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THE EFFECT OF ORDER FLOW ON THE NORDIC FOREIGN EXCHANGE RATES

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Abstract
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PURPOSE OF THE STUDY

The purpose of the study is to explain the short-term exchange rate movements and study the impact of different customer types' market activity on the foreign exchange rates. Furthermore, long-term relation between order flow and foreign exchange rates as well as the direction of causality are studied. The study expands current academic literature to new markets with more specific explanatory variables.

DATA

The data consists of customer transaction data gathered over a period of 2002-2008 from a large Nordic bank, holding substantial market shares. The data set includes over 1.4 million FX-Spot and FX-Outright transactions from that period, split between seven different customer types. Furthermore, the data set includes the country of origin of each customer. Some of the covered markets and customer types as well as the nationality of the customers are unique in the existing academic literature. Also short and long-term interest rate data from central banks and foreign exchange rates from Bloomberg are used.

RESULTS

The results of the study show that order flow clearly affects the determination of the foreign exchange rates. In all the markets under review, order flow and exchange rates have a long-term relation and furthermore, order flow also has clear short-term impacts on exchange rates. The models of the study can explain over 17% of the daily changes and over 90% of the monthly changes in the exchange rates. Furthermore, the results indicate that different customer types have different impacts on the foreign exchange rates. Moreover, order flow impacts the foreign exchange rates with a delay for some customer types. These lags vary between customer types. Finally, the results show no evidence of feedback trading i.e. the direction of causality runs from order flow exchange rates in the data set.

KEYWORDS

Foreign exchange, microstructure, order flow, causality, Nordic FX

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TUTKIELMAN TARKOITUS

Tutkielman tarkoituksena on selittää lyhytaikaisia valuuttakurssimuutoksia ja tutkia eri asiakasryhmien vaikutusta valuuttakursseihin. Lisäksi tarkoituksena on tutkia kauppavirran ja valuuttakurssien pitkäaikaista suhdetta toisiinsa sekä syy-seuraussuhdetta kauppavirrasta valuuttakursseihin ja toisinpäin. Tutkielma laajentaa nykyistä akateemista kirjallisuutta uusille markkinoille tarkemmilla selittävillä tekijöillä.

TUTKIELMAN AINEISTO

Tutkielman aineisto koostuu ison pohjoismaalaisen pankin asiakaskaupoista vuosilta 2002-2008. Aineiston markkinaosuus tutkituista markkinoista on huomattava. Aineisto sisältää yli 1,4 miljoonaa FX-spot ja FX-termiinikauppaa, jaettuna seitsemään eri asiakasryhmään. Lisäksi asiakkaiden kansallisuus on mukana aineistossa. Osa aineiston tutkituista markkinoista ja asiakasryhmistä sekä asiakkaiden kansallisuus ovat ainutlaatuisia olemassa olevassa akateemisessa kirjallisuudessa. Lisäksi pitkä- ja lyhytaikaista korkoaineistoa kansallispankeista ja valuuttakurssiaineistoa Bloomberg:sta on käytetty.

TULOKSET

Tutkielman tulokset osoittavat selvästi, että kauppavirta vaikuttaa valuuttakurssien määräytymisessä. Kauppavirralla ja valuuttakursseilla on pitkäaikainen suhde toisiinsa kaikilla tutkituilla markkinoilla ja kauppavirralla on lisäksi selkeitä lyhytaikaisia vaikutuksia valuuttakursseihin. Tutkielman selittävät tekijät selittävät yli 17 % päivittäisistä ja yli 90 % kuukausittaisista vaihteluista valuuttakursseissa. Lisäksi tulokset näyttävät, että eri asiakasryhmillä on erilainen vaikutus valuuttakursseihin. Edelleen, osalla asiakasryhmistä kauppavirran vaikutus valuuttakursseihin näkyy eripituisilla viiveillä. Lopuksi tuloksissa ei ole havaintoa palautekaupankäynnistä eli kauppavirta aiheuttaa valuuttakurssimuutoksia, mutta valuuttakurssimuutokset eivät aiheuta kauppavirtaa.

AVAINSANAT

Valuuttakaupankäynti, mikroteoria, kauppavirta, syy-seuraussuhde, pohjoismaiset valuutat

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1. Introduction

Meese and Rogoff (1983a) made breakthrough findings in explaining the exchange rate movements. Shortly put, they found that no macro model is superior to a basic random walk when estimating the foreign exchange (FX) rates. In the 1980s exchange rate economics was not able to find anything but near failures in the macro economic approaches to foreign exchange rates. The explanatory power of those macro models was next to none until Evans and Lyons (2002a) discovered their microstructure model using order flow as an explanatory factor for the foreign exchange rate movements.

Evans and Lyons (2002a) turned to microeconomics of asset pricing when macro fundamentals like interest rates and trade balances could not explain the movements in the foreign exchange rates. The microstructure models, however, are not a completely new side of the research; Glosten and Harris (1988), Madhavan and Smidt (1991), and Foster and Viswanathan (1993) have all used microstructure models in their empirical work concerning NYSE. In the 1990s the microstructure models were largely new to exchange rate economics and the most important variable in these models is order flow (Evans and Lyons, 2002a). Order flow and transaction volume are conceptually two different items. Order flow is volume that is signed. If the initiator of a transaction decides to sell 10 units, order flow takes a value of -10 whereas volume is 10. Order flow takes a negative value as the initiator chose to sell instead of buying those 10 units. Order flow can be measured over time and therefore, it is a measure of net buying pressure. In all microstructure models, order flow is the proximate determinant of price and essential to the transmission mechanism when mapping fundamental information to price.

The previous academic market microstructure research in the foreign exchange market has focused mainly on direct interdealer or brokered interdealer trading. The research, however, has not focused on trading between customers and market makers. To my best knowledge, only two such studies exist in this field: Fan and Lyons (2000) and Bjonnes et al. (2005). The reason for the scarcity of research in that area is the unavailability of data. This thesis uses a unique and the most comprehensive data set to date to confirm the existing results and expand the literature about market microstructure in the foreign exchange markets. Customer trading is considered central to the microstructure theory because customer orders act as catalysts causing a market response. Therefore, customer trading is the most potential source of order flow when explaining the foreign exchange rate movements.

The purpose of my thesis is to explain the short-term exchange rate movements and study the impact of different customer types' market activity on the foreign exchange rates. Macro economic literature has been able to explain a part of the long-term rate movements but the short-term movements were not explained until the advent of market microstructure in the late 1990s. The contribution of my thesis to the existing academic literature is that my unique data set allows me to study these microstructure effects more specifically than any of the previous studies. Furthermore, my thesis expands this microstructure theory to cover more markets, which have not been previously studied.

Since the first study of Richard K. Lyons on foreign exchange microstructure, the concept of order flow has been studied more widely but the focus has mainly been on the global main currencies, dollar, yen and euro. My thesis focuses on the Nordic currencies, Swedish krona, Danish and Norwegian krones and euro as well as on the U.S. dollar, expanding the academic literature to new foreign exchange markets. The data is gathered over a period of 2002-2008 from a large Nordic bank, which holds a market share up to 35% in these currencies, depending on the market. Furthermore, the data set is divided into seven different customer types, which makes it the most specific in the present academic literature on market microstructure. Moreover, I am able to specify the nationality of each customer in the data set and thus the results of this thesis are, to my best knowledge, the first in the foreign exchange literature to account for the customers' nationality. Prior to this thesis only two data sets have included as much customer trading data as my data set does. However, my data set is much more diversified in terms of different markets and market participants and therefore, it is exclusive and completely unique.

My empirical findings indicate that order flow clearly affects the determination of the FX rates. Over periods as long as three months, order flow explains most of the variance in the foreign exchange rates. In all studied markets, order flow and exchange rates have a long-term relation and furthermore, order flow also has clear short-term impacts on exchange rates. The results are based on a model where I have used both macro economic and microstructure determinants, such as interest rates and signed order flow[1]. The model bridges the macro economic research and the microstructure data together at all time horizons. My estimates can explain around 8%-9% of the daily changes in the exchange rates in the USD/EUR and DKK/EUR markets and around 14%-17% in the SEK/EUR and NOK/EUR markets. In comparison, the explanatory power of the traditional macro economic models is usually less than 10% at one- to twelve-month horizons. I have also studied the effect of order flow at the one- and three-month horizons and the results are extremely promising; the explanatory power of the model ranges from 88% to 96% at one-month horizon and exceeds 95% in all studied markets at three-month horizon.

I find that different customer types have different impacts on the foreign exchange rates. Corporate customers, state owned companies, public institutions and central banks act as liquidity providers at all studied time horizons and markets. The cumulative order flows of these customer types are negatively correlated with the foreign exchange rates. On the other hand, credit institutions and insurance companies are liquidity takers and their cumulative order flows are positively correlated with the foreign exchange rates. These findings are in line with the results of Bjonnes et al. (2005) and Fan and Lyons (2000), who have all found different impacts for different customer categories. Moreover, my results show that the short and long term interest rate differentials are positively correlated with the exchange rates. The empirical results also indicate that the effects of order flow on foreign exchange rates come at varying lags for some customer types. For instance, public institutions' order flow has an impact with a one-month delay in the DKK/EUR market whereas central banks have both contemporaneous and delayed impacts. Finally, I find no evidence of feedback trading, i.e. the direction of causality runs from order flow exchange rates in my data set.

The reminder of this thesis has seven main sections. Section 2 describes the features of the foreign exchange market to give the reader a good overview of the setting. Section 3 defines order flow in detail. Section 4 gives an overview of the related studies, focusing on microstructure studies. Section 5 presents the theoretical framework for this thesis as well as the hypotheses. Section 6 introduces the data set and addresses the issues of nonstationarity, Section 7 reports the empirical results of the empirical work and finally Section 8 concludes.

[1] End-user initiated currency buys (sells) are signed with positive (negative) values, which are aggregated at a customer type level over each 24-hour period, excluding weekends.

2. Features of the foreign exchange market

The foreign exchange market has two major differences compared to the features of other financial markets, such as the equity market. First, the foreign exchange market is a decentralized market with numerous individual market makers. Second, trading volume in the foreign exchange market is very large and carried out mainly among market makers. As an example of the very large volume, the daily average turnover of the global foreign exchange market surpassed 3.2 trillion dollars in April 2007 according to the Bank for International Settlements (BIS) (2007). In comparison, the daily average volume of all traded stocks in NYSE was 0.16 trillion dollars in January 2008 (NYSE, 2008). Table 1 below presents the global foreign exchange market turnover during the last 16 years (BIS, 2007).

Table 1 – Global foreign exchange market turnover

Daily averages in April 2007, in billions of US dollars

	1992	1995	1998	2001	2004	2007
Spot transactions	394	494	568	387	631	1,005
Outright forwards	58	97	128	131	209	362
Foreign exchange swaps	324	546	734	656	954	1,714
Total[1] turnover at April 2007 exchange rates[2]	880	1,150	1,650	1,420	1,970	3,210

This table presents the global foreign exchange turnover triennially since 1992, adjusted for local and cross-border double-counting. [1]Estimated gaps in reporting are excluded. [2]Non-US dollar legs of foreign currency transactions were converted from current US dollar amounts into original currency amounts at average exchange rates for April of each survey year and then reconverted into US dollar amounts at average April 2007 exchange rates

Due to its decentralized structure, it is difficult to find any statistics with institutional perspective about the foreign exchange market other than the data of BIS. BIS conducts triennially a snapshot of the market as individual central banks survey their financial institutions regarding foreign exchange trading activity for a single month. The BIS (2007) report states that roughly a third of the turnover comes from the spot market, a tenth from outright forward contracts and the rest from foreign exchange swaps, and that the four biggest traded currencies in April 2007 were US dollar, euro, yen and pound sterling with percentage shares of 86, 37, 17 and 15, respectively.[2] The most liquid currency pairs in April 2007 were euro/dollar, yen/dollar and sterling/dollar with percentage shares of 27%, 13% and 12%, of

[2] The sum of the percentage shares of individual currencies totals to 200% instead of 100%, as two currencies are involved in each foreign exchange transaction.

the global foreign exchange turnover, respectively (BIS, 2007). These percentage shares have little changed in the last decade expect that other currency pairs have gained share at the expense of yen/dollar. Furthermore, the market makers themselves are largely responsible for the enormous turnover in the foreign exchange market. According to BIS (2007), only 17% of the turnover is from transaction between dealers and non-financial customers. Finally, the trading between the market makers themselves accounts for over 40% of the turnover. Note that the foreign exchange swaps do not create any order flow. This is because an FX swap is a package of two equally sized but opposite foreign exchange transactions, one spot and one forward (it can also be a forward-forward, in which case the first forward has a shorter maturity than the second forward) and that is why foreign exchange swaps have been excluded from my data set.

2.1. Decentralization

The foreign exchange market is a decentralized market, where participants are physically separated from each other and transactions are made by telephone, telex or computer networks. Most of the interbank trading occurs through the computer networks called Reuters D3000 or Electronic Broking System (EBS), both established in 1992. Together they account for approximately 85% of the total interbank activity, with EBS dominating in all exchange rates other than the United Kingdom sterling and a couple of other currencies, according to Sager and Taylor (2006). The market has also experienced strong consolidation during the last decade. According to the BIS (2007) report, the number of banks accounting for 75% of the global foreign exchange turnover has more than halved in the United Kingdom, United States, Switzerland, Japan and Singapore. Nearly 70% of the foreign exchange turnover comes from these five countries, of which half from the United Kingdom.

2.2. Types of market participants

The participants in the decentralized foreign exchange market namely include market makers (typically a bank), brokers and customers. Generally a market maker is involved to the foreign exchange market and engaged in the buying and selling of different currencies, thus establishing a market for these currencies. They are committed to buy and sell i.e. to make a "two-way" price for particular currencies against one another. The interdealer foreign exchange market has a hybrid market structure with two alternative trading channels: direct (bilateral) and brokered (including both electronic brokers and voice brokers). Banks approach each other during trading in the direct market, and the bank receiving a call acts as a market maker for the currency pair to be traded by offering a two-way quote i.e. both bid and ask prices. The quotes are take-it-or-leave-it and must be dealt or declined within seconds. A detail of these direct transactions, such as bid and ask quotes, is that the amount or the direction of the trade are only observed by the two transacting counterparties. According to Sager and Taylor (2006), the core function of these market makers is to facilitate access for customers to interdealer liquidity and provide best execution for customer trades.

The brokered market, however, is more transparent. Electronic brokers, such as EBS, broadcast best bid and ask prices and the direction of all transactions. This information, however, is only available to the market makers. Electronic brokers were introduced in 1992 and have become dominant in the interdealer trading. It may be clarifying to note that brokers only match dealers in the interbank market without being a counterparty of any transaction and without taking any positions. There are a couple of reasons why dealers choose to use brokers instead of trading directly with each other. First, a dealer may not want to reveal his identity before the transaction is executed. Second, providing a broker with a limit order gives the dealer a wider advertisement of a willingness to buy or sell than using bilateral direct quoting. Furthermore, it is notable that participating in the brokered market is voluntary, but dealers in the direct market are committed to quote a price at which they are willing to trade.

Customers interact with dealers to access the liquidity of the interbank market, according to Sager and Taylor (2006). Voice trading is the most active channel of this interaction, but several recently introduced electronic platforms have been growing rapidly in this customer-dealer space. Customer activity in the foreign exchange market relates to currency exposure management in investment portfolios, except for corporate hedging of translation risk of the foreign currency income and costs.

According to Sarno and Taylor (2001), the direct foreign exchange market can be classified as decentralized, but the brokered market may be categorized as quasi-centralized as each FX broker accumulates a subset of market makers' limit orders, which is an order to either buy or sell a definite amount of currency against another currency at a predefined exchange rate.

2.3. Fragmentation of the foreign exchange market

The decentralization discussed in the previous paragraphs is probably the biggest difference of the foreign exchange market compared to the equity market, for example, as in a centralized market – such as NYSE – trade is carried out at a publicly announced price. Furthermore, all traders in a centralized market face exactly the same trading opportunities whereas in a decentralized structure, prices are quoted and transactions executed in private, bilateral meetings. The decentralization of the foreign exchange market has one important consequence, fragmentation. The fragmentation of the market strongly distinguishes the foreign exchange market from other financial markets. This is because transactions of the same product (a SEK/EUR spot transaction, for example) may occur at the same time at different prices as not all dealer quotes are observable. In addition, the foreign exchange market has less transparency than other financial markets as there are no disclosure requirements in the FX market and thus, transactions are not observable. This feature is rather important from a theoretical perspective, as order flow can transmit information about fundamentals. If this order flow is not generally observable, then the process of trading will be less informative and the information reflected in the foreign exchange rates will be reduced.

We must also take into account that trading in the foreign exchange market does not stop at any moment; it is continuous around the clock, as opposed to a call market, such as the equity market where the participants are called upon.

The following Section 3 describes and defines order flow in detail. Also customer order flow is defined apart from general order flow.

3. Defining order flow

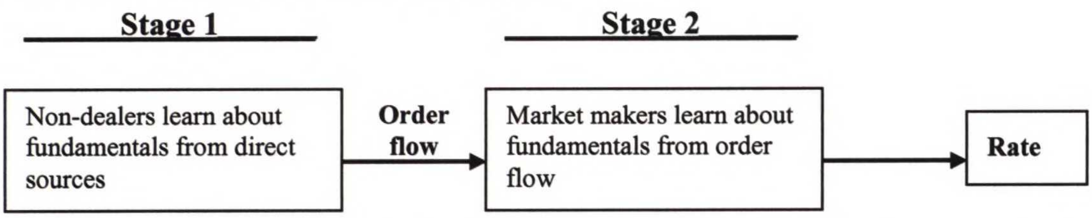
When moving from the macro approach to microstructure models a key variable, order flow, which does not have any role in the macro approach, takes a central place. It is essential to understand order flow as a concept to be able to comprehend how the microstructure models differ from the earlier macro approaches. Centrally, order flow and transaction volume are not the same. Order flow is volume that is signed. If a customer approaches a dealer (market maker, usually a bank) and decides to sell 10 units (for example, Swedish kronas), order flow is -10 whereas transaction volume is 10. As the initiator of the transaction (the customer) is selling, order flow takes on a negative value. Remember that the dealer (market maker) is on the passive side of the trade and the transaction is signed according to the active, or aggressive, side of the trade. When measuring order flow over time, it can be calculated as the sum of the signed buyer-initiated and seller-initiated trades. Therefore, a negative sum means net selling pressure over the period in question. Despite the fact that every transaction involves a seller and a buyer, the theory of microstructure has a way of attaching a sign to each transaction when measuring order flow.

According to Lyons (2001), order flow is a variant of excess demand in microstructure finance. Rather than being a synonym to excess demand, it is a variant for two reasons. First, as there are two counterparties to every trade, by definition excess demand equals zero in equilibrium. For order flow, this is not the case. As the foreign exchange market is a decentralized market, orders are initiated against a dealer or a market maker who is ready to absorb imbalances between the buyers and the sellers of a foreign currency. According to Lyons (2001), these uninitiated dealer transactions drive a wedge between order flow and excess demand. Second, order flow is distinct from demand, because it measures actual trades, and demand shifts as a concept do not need trades. For example, in the earlier macro approach models the demand shifts move prices without trades ever needing to occur. Of course, in the microstructure models order flow is the key variable moving foreign exchange rates.

Order flow clearly plays a central role in the microstructure models across the board. As order flow has this across the board property it expands the applicability of microstructure a great deal. Remember that in the traditional asset approach models order flow has no role; it does not explain foreign exchange rate movements. As all microstructure models have order flow as a key variable it is plausible to say that microstructure conceptually is “a new lens for viewing markets”, according to Lyons (2001).

Fig. 1 below illustrates a very important feature of microstructure models, which relates directly to order flow according to Lyons (2001). Fig. 1 presents how information processing has two stages. Firstly, fundamentals are observed and analysed by non-dealer market participants i.e. the customers. Secondly, market makers interpret this analysis of fundamentals through order flow and set price accordingly.[3]

Figure 1 – Two stages of information processing



In stage 1, fundamentals are observed and analysed by non-dealer market participant. In stage 2, the analysis made in stage 1 is interpreted by market makers. Finally, the foreign exchange rate is set accordingly by market makers.

According to Lyons (2001), "order flow conveys information about fundamentals because it contains the trades of those who analyze fundamentals". Obviously, separating the trades with information from the uninformative trades is difficult, if not impossible. Clearly, it is too bold to state that the market maker does not learn anything from the fundamentals that she does not learn from order flow, as suggested in the standard microstructure models. The market maker's dependence to learn from order flow arises in these standard models because the learned information is private. Similarly, the dealers need not to learn from order flow if the information is publicly known. However, as some information relevant to foreign exchange rates is private and some is public, learning from order flow can be important.

3.1. Customer order flow

Although private information is not significant in the usual sense in the foreign exchange market, private information exists. According to Yao (1998), the most important type of private information is order flow. And within different types of order flow, market maker's customer order flow is the most important source of private information as it reflects demands from capital flow and from international trade. Moreover, Yao (1998) finds that any private information in the foreign exchange market exists only for less than 30 minutes, leaving market makers only a short window of opportunity to capitalize on such private information. Furthermore, Lyons (1995), Bjonnes and Rime (2005) and Ito et al. (1998) also state that

[3] Stating that market makers learn only from order flow is too strong. This arises in the standard microstructure models as they assume that all information is non-public i.e. private. Traditional macro models, however, go to the other extreme stating that all information is public and available to every market participant simultaneously.

customer order flow is the most important source of private information in the foreign exchange market. Finally, according to Bjonnes and Rime (2001), the sign of the customer trades is more informative than the associated nominal of the trade

According to Yao (1998), customer trades are important in the foreign exchange market as they embody the major source of asymmetric information, and they often generate a considerable portion of the profits for market makers. The reason why customer trades are the source of asymmetric information is that the market maker does not have direct information about the customer trades of other market makers due to the lack of transaction reporting requirements. His results of finding no shade quoting (i.e. raising quotes when the market maker is short relative to her desired position and lowering quotes when she is long) support this as the market makers avoid revealing their learned private information.

Cheung et al. (2004) conducted a survey among market makers in the United Kingdom and when they asked the market makers to select the technique that best characterized their dealing method, customer order-driven technique was the most popular dealing method, selected by nearly 40% of the respondents. This finding also supports the importance of customer order flow.

In the microstructure theory, the role of customer order flow is essential. This is borne out of the following theoretical discussion: customer order flow is the catalyst in the foreign exchange market resulting in market response. Also the above findings of the Cheung et al. (2004) survey support what Lyons (2001) states: One foreign exchange trader said that customer trades are the market's "crack cocaine", meaning that the customer orders are the market's catalyst and quite powerful catalyst indeed. Moreover, according to Lyons (2001) "proprietary information on customer flows is a prime driver of proprietary trading at the largest banks". As a contrast, smaller banks have too little customer order flow to make use of the information it may convey. Lyons (2001) continues stating that customer order flow information is considered valuable for predicting foreign exchange rate movements by banks. This fact adds a totally new dimension to the theory of order flow and microstructure models. Also, this predictive power that today's customer order flow can predict future movements of the exchange rates is the most interesting part of the microstructure approach to many practitioners. The explaining of movements, however, is still very interesting to many people with academic or economic background.

A big problem for past research on customer order flow has been the data scarcity. The only possible source of customer data is the private banks themselves but usually banks are not keen on providing this information. Therefore, the early microstructure research focused only on order flow between market makers. However, Fan and Lyons (2000) were able to obtain customer transaction data from Citibank, a leading foreign exchange trading bank (Lyons (2001) estimates its market share to be in the 10-15% range). That data is available only on a time-aggregated basis and therefore does not include individual transactions. Furthermore, Bjonnes et al. (2005) obtained 90-95% of all worldwide trading in Swedish krona (SEK) covering a period January 1993 to June 2002 from the Swedish central bank, Riksbank. The data scarcity is the reason why the majority of foreign exchange order flow research is done with the interdealer data and to my knowledge only the above two data sets have been used to study customer order flow[4].

What makes the customer order flow so fascinating is that the customers represent the underlying demands in the economy. According to Lyons (2001) the customers are the market participants, whose demand shifts matter for persistent price movements. Furthermore, with this customer order flow data I can separate the order flow components to "current account intensity" and "capital account intensity" as Fan and Lyons (2000) do. This is possible as my data set has a customer type attached to each transaction and the trades of non-financial corporations can be separated from financial corporations. These non-financial corporation trades include the demand from current account transactions and the trades of the financial corporations include the demand from capital account transactions. Being able to separate order flow based on the customer type I am able to test whether the price impact of these customer types is different from each other.

The next Section 4 gives an overview of the related studies. The traditional macro models are only looked upon briefly and more focus is casted on the past microstructure literature. In addition, research on the causality issue is overviewed.

[4] The data set of Yao (1998) had substantial customer order flow, but his data set covered only 25 trading days from only one dealer. Furthermore, FXFX quotes have been used to study microstructure theory but the quotes are only indicative and therefore their reliability is considerably lower.

4. Overview of related studies

Explaining and forecasting the movements of foreign exchange rates has been a significant point of interest since many of the large industrialized economies let their exchange rates floating in the early 1973, after the downfall of the Bretton Woods system of fixed exchange rates. Furthermore, exchange rate economics has been one of the most active areas of economic research at least until the mid 1990s. Nevertheless, it took over 20 years for the researchers to develop a model, which would be superior to a basic random walk model at short horizons. This overview of the related studies analyses and summarizes several different articles; some of them explaining the FX movements with the traditional macro economic models and some using microstructure models in explaining the foreign exchange rates.

4.1. Explaining foreign exchange movements with traditional macro models

One of the great studies of the early 1980s is the study of Meese and Rogoff (1983a): Empirical exchange rate models of the seventies. They compare time series and structural models of exchange rates on the basis of their out-of-sample forecasting accuracy. Meese and Rogoff (1983a) find that a random walk model predicts major-country exchange rates as well as any of their candidate models. Each of their competing, candidate models are used to generate forecasts at one to twelve month horizons for the dollar/pound, dollar/Deutsche mark and dollar/yen exchange rates. As representative structural models they choose the flexible-price monetary model and the sticky-price monetary model among others and estimate these using the ordinary least squares (OLS), generalized least squares, and Fair's (1970) instrumental variables technique as well as a variety of univariate time series techniques.

Later, in 1983 Meese and Rogoff (1983b) studied the exchange rates movements in a longer period and found that the relative superiority of the random walk model over the structural models diminishes as the forecast horizon gets closer to twelve months. However, their findings are of an unstable fashion; the best coefficient values bounce around depending on the forecast horizon and thus, no single model outperforms the random walk model consistently. Because of these findings of Meese and Rogoff (1983a, b), the simple random walk model of the exchange rate has become the standard benchmark for empirical exchange rate performance.

4.2. Non-linear macro models

Meese and Rogoff (1983a) make no attempt to account for possible non-linearities in the underlying models. That may be the reason for their failure to prevail the random walk model in the 1980s. Later in the 1990s Chinn (1991), Chinn and Meese (1994) and Mark (1995) were able to construct models, which outperformed the simple random-walk model at least on some longer forecasting periods.

Chinn (1991) uses both linear and non-linear models as variants of the sticky-price monetary model with interest rates, consumer price index and real GNP (seasonally adjusted) among others as variables. Furthermore, Chinn and Meese (1994) examine the predictive performance of four structural exchange rate models using both parametric and non-parametric techniques. Also, Mark (1995) presents evidence of an economically significant predictable component in long-horizon changes in log exchange rates.

Chinn's (1991) research concludes that non-linear forecasts yield substantial improvements over a random walk except over one-quarter forecast horizons where random walk still dominates. Also, the non-linear models do slightly better than their linear competitors. The findings of Chinn and Meese (1994) state that random walk model prevails for short-term prediction horizons but for longer horizons (12, 24 and 36 months), some (but not all) of their models do significantly better than a random walk model in explaining the exchange rate movements of the Deutsche mark and yen relative to dollar. The evidence of Mark (1995) relies on regression of long-horizon changes in log exchange rates on the current log exchange rate's deviation from a linear combination of log relative money stocks and log relative real income. Mussa (1979) makes the points, among others, that "the log of the spot rate is approximately a random walk" and that "most changes in exchange rates are unexpected". Against this evidence by Mussa, Mark's (1995) findings are noteworthy as prior to his study it had long been thought that log exchange rates are unpredictable. However, it is important to note that Mark's (1995) strongest evidence against the unpredictability of log exchange rates comes at the horizon for which he has the fewest observations, the 16-quarter horizon.

The findings of Meese and Rogoff (1983a) and later that year by the same authors had a "pessimistic effect on the field of empirical exchange rate modelling in particular and international finance in general" as Frankel and Rose (1995) state. Their analysis at short horizons, less than 12 months, had never been credibly overturned or explained until the late 1990s. However, no matter how pessimistic the views for empirical exchange rate modelling were, both Frankel and Rose (1995) and Taylor (1995) felt somewhat optimistic about the course of future research in this area, "in part because of the prospects of new developments that analyze the market for foreign exchange primarily from a microeconomic perspective."

4.3. The advent of microstructure models

Microstructure modelling had already been used in the equity markets, but Lyons's (1991) pioneering study was the first to apply microstructure to the foreign exchange market. It models the source of information asymmetry among dealers using customer order flow. This information asymmetry arises from the features of the foreign exchange market where there is no centralized exchange, rather a decentralized network of traders. The main result of the study is that the greater the market power and risk-aversion of dealers, the less revealing are prices.

Lyons (1995) continues to investigate these issues and finds strong, novel evidence of an inventory-control effect on price. His data set is qualitatively different from anything in the exchange rate literature at that time; it contains actual transactions prices and quantities covering five trading days in August 1992. The alternatives, such as in Goodhart and Figliuoli (1991), Bollerslev and Domowitz (1993) or Bessembinder (1994) are constructed from so called "indicative quotes", input to Reuters by trading banks. The data set of Lyons (1995) overcomes three key shortcomings of the indicative quotes: First, indicative quotes are not binding prices, i.e. they are not transactable. Second, there is no measure of order flow or transaction prices. And finally, according to Lyons (1995) the dealers at major banks do not pay any attention to the indications and thus, the indications may not transmit any asymmetric information. As well as the abovementioned inventory-control effect on price, Lyons (1995) finds evidence of another channel whereby trading volume generates movements in the FX rates: the information channel, i.e. if some traders have superior information than others, it is rational for these market makers to adjust their price quotes, in response to order flow. Specifically, according to the findings of Lyons (1995), this information asymmetry induces dealers to decrease price about 0.0001 DM/$ for every incoming sell order of $10 million (conversely for buy orders).

Yao (1998) studies the market making behaviour of FX dealers in the interbank market with a data set covering 25 trading days at a major commercial bank. He finds similar evidence as Lyons (1995) that incoming trades have information effects. His data set consists of complete trading records of a major market maker who has substantial customer flows over the sample period. Yao finds little evidence of quote-shading as a tool for inventory control. The customer trades may be the reason for that as quote-shading (raising quotes when the dealer is short relative to his desired position and vice versa) signals dealer's position and further reveals information from his proprietary order flows. Yao's findings complement Lyons's (1995) evidence of inventory-control effect on price as the data set of Lyons (1995) does not include any customer trades and thus, has a relatively low degree of private information. Finally, Yao (1998) finds that large trades have significant lagged price impacts.

Later Bjonnes and Rime (2005) studied dealer behaviour in the FX spot market using detailed observations on all the transactions of four interbank dealers for a period of five days in March 1998. Similarly to the findings of Yao (1998), they do not find evidence of inventory-control through dealers' own prices as predicted by the inventory model similar to the model used by Lyons (1995). Bjonnes and Rime (2005) also find strong support for the information effect in incoming trades and thus, the information asymmetry issue is further confirmed since cumulative order flows and price levels are cointegrated. Furthermore, they find that information effect increases with trade size in direct, bilateral trades. More specifically, they find that an additional purchase of dollars with Deutsche mark will increase the Deutsche mark price of dollar by approximately 1 pip[5], which is at the same level than in the Lyons (1995) study. Finally, the results of Payne (2003) concerning the price effect are similar to those of Lyons (1995) and Bjonnes and Rime (2005).

[5] One pip equals one price tick or a change of 0.0001 in the price of an asset.

4.4. Information aggregation in microstructure

The study of Evans and Lyons (2002a) presents a new kind of exchange rate model, which was instantly strikingly successful in explaining the exchange rate movements in horizons less than 12 months. It took 20 years to overcome the pessimistic effect stated by Frankel and Rose (1995). Evans and Lyons (2002a) use a data set, which includes all the Deutsche mark and yen transactions against dollar over a four-month sample from May 1 to August 31, 1996, on an interdealer trading system called Reuters Dealing 2000-1. Their findings show that order flow and nominal exchange rates are strongly positively correlated thus indicating the price decreases with selling pressure. The model of Evans and Lyons (2002a) explains more than 60% and 40% of daily changes in the log Deutsche mark/dollar and log yen/dollar exchange rate, respectively.

The analysis of Evans and Lyons (2002a) fills the gap between the 1990s microstructure research of tick-by-tick data and the 1980s and the 1990s macro research using monthly data. They do this by developing a model that specifies how interdealer order flow drives foreign exchange rate determination via information aggregation. This aggregation is done by calculating a daily net sum of order flow of signed interdealer trades, which is used as an explanatory factor. As another component, the model includes the change in the nominal interest differential as that is the main engine of exchange rate movements in the traditional macro models (Evans and Lyons, 2002a). The strikingly successful model of Evans and Lyons (2002a) is:

$$\Delta p_t = \beta_1 \Delta(i_t - i_t^*) + \beta_2 \Delta x_t + \varepsilon_t, \qquad (1)$$

where Δp_t is the change in the log spot rate, $i_t - i_t^*$ is the nominal interest rate differential (i_t is the nominal dollar interest rate and i_t^* is the nondollar interest rate) and x_t is order flow. According to Evans and Lyons (2002a), using the change in the spot rate, ΔP_t, produces nearly identical results, yet log spot rate is chosen as the dependent variable to make the model comparable to standard macro models. Table 2 below presents the results of their study.

Table 2 – Model estimates

Currency pair	$\Delta(i_t\text{-}i_t^*)$	Δx_t	R^2
Deutsche mark/dollar	0.51 (0.26)	2.14 (0.29)	0.64
Yen/dollar	2.47 (0.92)	2.86 (0.36)	0.46

The above table presents the ordinary least squares (OLS) estimates of the Evans and Lyons (2002a) model, $\Delta p_t = \beta_1\Delta(i_t\text{-}i_t^*) + \beta_2\Delta x_t + \varepsilon_t$, where Δp_t is the change in the log spot exchange rate from day t-1 to day t, $\Delta(i_t\text{-}i_t^*)$ is the change in the one-day interest differential from day t-1 to day t and Δx_t is the interdealer order flow from day t-1 to day t (negative for net dollar sales, in thousands). Standard errors are shown in parentheses (corrected for heteroskedasticity in the case of the Deutsche mark). The sample data is from May 1 to August 31, 1996.

The explanatory power of the model comes from the order flow component. According to Evans and Lyons (2002a), regressing log spot rate only on the nominal interest rate differential produces an R^2 statistic at 1% or lower for both Deutsche mark/dollar and yen/dollar regressions with insignificant coefficients. Furthermore, the results are consistent with estimates of both Lyons (1995) and Bjonnes and Rime (2005). They both find a price increase of approximately 1 pip or 0.0001 Deutsche mark/dollar for an additional buy order of \$10 million i.e. 0.01 DM or 1 pfennig per \$1 billion. In the study of Evans and Lyons (2002a), the coefficient of 2.1 in the Deutsche mark/dollar equation indicates a Deutsche mark price increase of a dollar by 2.1% on a day with 1,000 more dollar purchases than sales. As the average trade size in the data sample of Evans and Lyons (2002a) is \$3.9 million, 1 billion of net dollar purchases increases the DM price by 0.54% (= 2.1/3.9) or 0.8 pfennig.

The findings of Evans and Lyons (2002a) hint that the foreign exchange market is aggregating information even though the traditional macro models admitted no role for that. Also their estimates are in line with the estimates of Lyons (1995) and Bjonnes and Rime (2005) at the level of individual dealers. According to Evans and Lyons (2002a), the reason why order flow seems to explain the foreign exchange rate movements so well is that order flow proxies for changes in the interest rate differential expectations of individuals. It is important to note about the studies of Lyons (1995) and Bjonnes and Rime (2005) that they are conducted on a high-frequency, trade-to-trade basis compared to the study of Evans and Lyons (2002a), where the data is aggregated on a daily basis. Finally, all these three studies explain the foreign exchange rate movements with interdealer order flow.

4.5. The long-run impact of order flow

The brokered interdealer trading has also been studied previously. Killeen et al. (2006) present evidence that cumulative order flow and the French franc/Deutsche mark spot rate are cointegrated. They use data from January to December 1998, provided by EBS to prove that after the conversion rates for the euro-participating currencies were announced in early May 1998, the FF/DM rate was decoupled from order flow. More explicitly, they find that net Deutsche mark purchases of 1 billion increase the FF/DM exchange rate by three basis points, which is much smaller an impact than found by Evans and Lyons (2002a).

Three factors explain the differences in the impact found by Killeen et al. (2006): First, they measure the impact per billion DM, not per billion dollars. Second, Killeen et al. (2006) measure the long-run impact, i.e. the persistent impact, whereas Evans and Lyons (2002a) measure the impact effect. And finally, according to Killeen et al. (2006), one would expect the sensitivity of price to order flow to be lower in the FF/DM market exactly because the EMS target zones were not a free float. Instead, the currency fluctuations of the bilateral exchange rates were required to stay within a band of 2.25% around a grid of central parities (Giavazzi and Giovannini, 1989).

4.6. Customer order flow

Fan and Lyons (2000) study customer order flow and find that aggregate customer order flow tracks exchange rate movements rather closely at monthly frequencies. He finds that a net purchase of one billion euros increases the USD/EUR rate by 0.8%. Similarly, a net purchase of one billion dollars increases the Japanese yen/dollar price by 1.2%, roughly twice the size estimated by Evans and Lyons (2002a). Furthermore, he disaggregates the customer order flow into three different customer components and finds that the three components have different price impacts. Notable, the price impact of leveraged and unleveraged financial customer is positive, while for non-financial customers the impact is negative. At the same time, the model's fit roughly doubles compared to the univariate model without disaggregation of the customer types.

Similarly to the study of Lyons (2001), Bjonnes et al. (2005) study the price impact of four customer groups: market making banks, financial customers, non-financial customers and central bank (Sveriges Riksbank). They find that an increase of one standard deviation, i.e. 12 billion Swedish kronas, to the order flow of financial customers implies an increase of 0.66% to the SEK/EUR exchange rate at a 30-day horizon, which is economically significant. As oppose to this, similar increase to the order flow of non-financial customers implies a decrease of similar size to the SEK/EUR exchange rate. Furthermore, according to Osler (2006), many other studies have found this same link at short horizons, while there is no disconfirming evidence in the existing academic literature. Therefore, it can be considered a conventional fact, that cumulative financial order flow is positively cointegrated with foreign exchange rates, while the reverse is true for cumulative commercial order flow.

4.7. Causality

Evans and Lyons (2002b) examine the issue of causality (i.e. whether order flow drives foreign exchange rates or vice versa) in their study. They state that the direction of causality runs from order flow to price in their model and generally that is true in the microstructure theory. The direction of causality holds also in all the generally recognized models even though price and order flow are determined at the same time (Glosten and Milgrom, 1985; Kyle, 1985; Stoll, 1978; and Amihud and Mendelson, 1980). The alternative for this direction of causality is reverse causality, i.e. feedback trading. Evans and Lyons (2002b) begin by stating that most of the models of feedback trading are supported by non-rational behaviour, making them less attractive to many researchers on a priori grounds. These models generally require forecastable returns using lagged returns. However, this requirement is not a property of major floating exchange rates and neither a property of their hourly data set.

According to Evans and Lyons (2002b), “existing empirical evidence on feedback trading in foreign exchange is scant”. This also supports the non-rational behaviour and hints that reverse causality is not the case in foreign exchange microstructure. Furthermore, Evans and Lyons (2002b) find no evidence of feedback trading in their intra-day data sample. Killeen et al. (2006) use daily data to study the direction of causality on foreign exchange order flow and find that returns do not Granger cause order flow but order flow Granger causes returns, providing a piece of relevant evidence.

Moreover, Evans and Lyons (2001) study the direction of causality and find that causality runs strictly from order flow to price under the null hypothesis of their model. They form three timing hypotheses, called the Anticipation hypothesis, the Pressure hypothesis and the Feedback hypothesis, in which the reverse causality becomes a problem only under the Feedback hypothesis under certain conditions. They test, using daily data, whether positive-feedback trading (i.e. systematic buying in response to price increases and selling in response to price decreases) is present in their data. If that would be the case, one would expect order flow in period t to be positively related to the price change in period $t-1$. They find past price changes insignificant and not reducing the significance of order flow in period t and thus, positive-feedback does not exist in their data at the daily frequency.

The following Section 5 presents the theoretical framework, which my thesis is based on. The theory of macro models is touched briefly while the focus is on microstructure.

5. Theoretical framework

5.1. Theory of the earlier macrostructure models

The earliest approach to the exchange rate determination was the goods market approach before the 1970s. The implication of the goods market approach is somewhat intuitive: trade surplus creates demand for the currency, which leads to appreciation. In other words, the currency demand comes from the sale and purchase of goods. Even though this may sound as a rational expectation, the data proves this theory insufficient. Trade balances are almost completely uncorrelated with foreign exchange rate movements in the major-currency FX markets.

The second exchange rate determination approach became known in the 1970s: The asset approach. This asset approach acknowledges that the sale and purchase of goods is not the only factor moving exchange rates. Therefore, assets were introduced to the models. Lyons (2001) has a very good example of this asset approach: "In order to purchase a Japanese government bond, a U.S. investor first purchases the necessary yen. In addition, the investor's dollar return will depend on movements in the yen, so his demand for the bond depends in part on his desire to speculate on those currency movements". Compared to the goods approach, these asset approach models incorporate the idea that public information is useless for producing excess returns as the exchange rate market is seen as efficient.

Unfortunately, also these models failed. Meese and Rogoff (1983a) prove that the asset approach fails to explain major-currency foreign exchange rates better than a simple "no-change" model. Later, in the 1990s Meese (1990) summarizes that "the proportion of (monthly or quarterly) exchange rate changes that current models can explain is essentially zero." Also, Frankel and Rose (1995), Isard (1995) and Taylor (1995) among others have made massive surveys to show this poor empirical performance of the asset approach models. These models also had some other problems. They cannot explain the enormous trading volume of the foreign exchange market at all, as the actual transactions have no role in mapping the economic variables into foreign exchange prices. Furthermore, the models assume homogenous beliefs and interpretation of the news, so that differing beliefs cannot be the driver of trading. However, most economists agree that the macro models are not erroneous. Instead of being erroneous, the asset approach models may just lack some key characteristics, which would explain the foreign exchange rate determination and movements.

5.1.1. Structural macroeconomic models

The models of the macroeconomic approach typically try to explain foreign exchange rates on a monthly frequency. They take the following form:

$$\Delta P_t = f(\Delta i, \Delta m, \Delta g, \ldots) + \varepsilon_t, \tag{2}$$

where ΔP_t is the change in the foreign exchange rate between the months *t-1* and *t*. The regression function has several different macro economic variables such as the difference between the home and foreign interest rates Δi, differences of the money supply, Δm or of the GDP growth rate, Δg and other macro variables denoted by the ellipsis. Note here that there is no space for transaction data or order flow. Therefore the error term ε_t subsumes all the information the transaction data may have. The logic of these models is coherent, and intuitively they seem appealing. The past research using these macroeconomic models, however, cannot explain more than a small fraction of the monthly variation in the floating foreign exchange rates (Frankel and Rose, 1995; Isard, 1995; Taylor, 1995).

5.2. Microstructure theory

5.2.1. The difference between macro and micro models

One basic fundamental difference lies in all microstructure and macroeconomic models; the information role of trades in price determination. In the traditional macro models the transactions did not have their own distinct variable and therefore were without any distinct role. The variables in the established macro models consist only of macroeconomic data; interest rates, money supply etc. In microstructure models, however, the transactions themselves have a leading role and they are treated as the cause of the foreign exchange rate movements.

According to the traditional macro economic models, order flow should not affect the foreign exchange rates. These models are based on two major assumptions;

(1) All exchange rate relevant information is common knowledge and
(2) the effect of the knowledge on the FX rates is also publicly known

As a result, the macro economic models basically assume that all macro economically relevant information is instantaneously public and mapped to the currency rates without the need of order flow. Order flow, however, has price related information if these assumptions do not hold. Also previous research has found that order flow carries relevant information.[6]

Macro fundamentals, however, can be the actual underlying determinant of the exchange rates even when order flow is considered as a proximate determinant of exchange rates. It could be that the macro fundamentals are an imprecise measure in exchange rate models and order flow presents a better proxy of the variation of exchange rates. The standard empirical measures of expected future fundamentals are imprecise, which makes the interpretation of order flow as a proxy for macro fundamentals reasonable. The reasoning for this logic is as follows: Expected future fundamentals are based on surveys whereas order flow reflects one's willingness to bank one's belief with money. It is the same than counting the backed-by-money expectational votes (Evans and Lyons, 2002a).

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[6] Lyons, 1995; Yao, 1998; Covrig and Melvin, 2002; Ito et al., 1998; Cheung and Wong, 2000; Bjonnes and Rime, 2005; Evans, 1999; Naranjo and Nimalendran, 2000; and Payne, 2003 among others.

5.2.2. Microstructure models

Lyons (1995) was a pioneer to develop the microstructure approach in the exchange rate determination. Later in the 21^{st} century, together with Evans, he presented a model which was able to explain more than 60% of the daily changes in the log Deutsche mark/dollar exchange rate (Evans and Lyons, 2002a). This microstructure approach is still based on the sale and purchase of assets but it relaxes three assumptions of the asset approach (Lyons 2001):

1. Information: microstructure models recognize that some information relevant to exchange rates is not publicly available.
2. Players: microstructure models recognize that market participants differ in ways that affect prices.
3. Institutions: microstructure models recognize that trading mechanisms differ in ways that affect prices.

The key relaxation of the microstructure approach is the first one concerning information. It can be empirically proven that all information relevant to foreign exchange rate determination simply is not publicly available. My thesis concentrates on analyzing the consequences of this using the microstructure tools.

Some easy-to-understand examples propose that the Lyons (2001) relaxations are on target. Foreign exchange traders at banks constantly see information (incoming customer trades) which is not publicly available. As my thesis indicates, this information forecasts the subsequent foreign exchange rates. Also, interpreting publicly available information is not linked to the foreign exchange rates similarly as the market participants interpret the public information differently. Finally, in low-transparency foreign exchange markets updating of beliefs about correct rates can be slow, thereby altering the path of realized prices.

Within the microstructure approach, foreign exchange rate determination equations are derived from the optimization problems the dealers i.e. the price setters, are facing. All the microstructure models are variations of the following equation:

$$\Delta P_t = g(\Delta I, \Delta X, \ldots) + \varepsilon_t, \qquad (3)$$

where the ΔP_t is the nominal foreign exchange rate difference between transactions instead of the difference at a monthly level as in the macro approach models. The variables in the function $g(\Delta I, \Delta X, \ldots)$ include the change in the dealers inventories i.e. net positions ΔI and the signed order flow ΔX among other micro variables denoted by the ellipsis. Here the signed order flow ΔX can have both negative (-) values when the counterparty sells against the dealer's bid or positive (+) values when the counterparty buys against the dealer's ask price. I have used a convention that positive order flow X equals net euro purchases by the passive side of the trade. This makes the theoretical correlation positive: net euro purchases drive the foreign exchange rates up. Note that here the error term ε_t is the opposite compared to the error term of the macroeconomic models: the error term in the microstructure model subsumes all the macro variables that make the function $f(\Delta i, \Delta m, \Delta g, \ldots)$ in the macroeconomic models whereas the error term in the macro approach subsumes the function $g(\Delta I, \Delta X, \ldots)$ of the microstructure models. Therefore, the residual of the microstructure model is a mirror image of the residual of the macro approach model in that it subsumes any foreign exchange rate movement due to the publicly available information variables of the macroeconomic model.

The key element spanning the difference between the microstructure and macroeconomic models is the signed order flow X. The past microstructure models have been uniformly able to show positive correlation between the price ΔP_t and the order flow ΔX because the order flow conveys information, which is not publicly known, with it. This can then be impounded in the foreign exchange rate. Once this information is communicated it has its effect on the price: if an agent with superior information about the value of some asset exists, that information advantage encourages the agent to trade. Then, a dealer can learn from such trades (asset purchases indicate positive news about the asset, and vice versa). Earlier studies in many different securities markets, including foreign exchange, stocks and bonds (Bjonnes and Rime, 2005; Snell and Tonks, 1995; and Vitale, 1998, respectively), have all found positive, significant relation between ΔP_t and ΔX at the transaction frequency. Note that such empirical testing has been possible only a relatively short time period. As electronic trading has established its current status more detailed records of order flow have become available for research.

5.3. The model – a hybrid approach

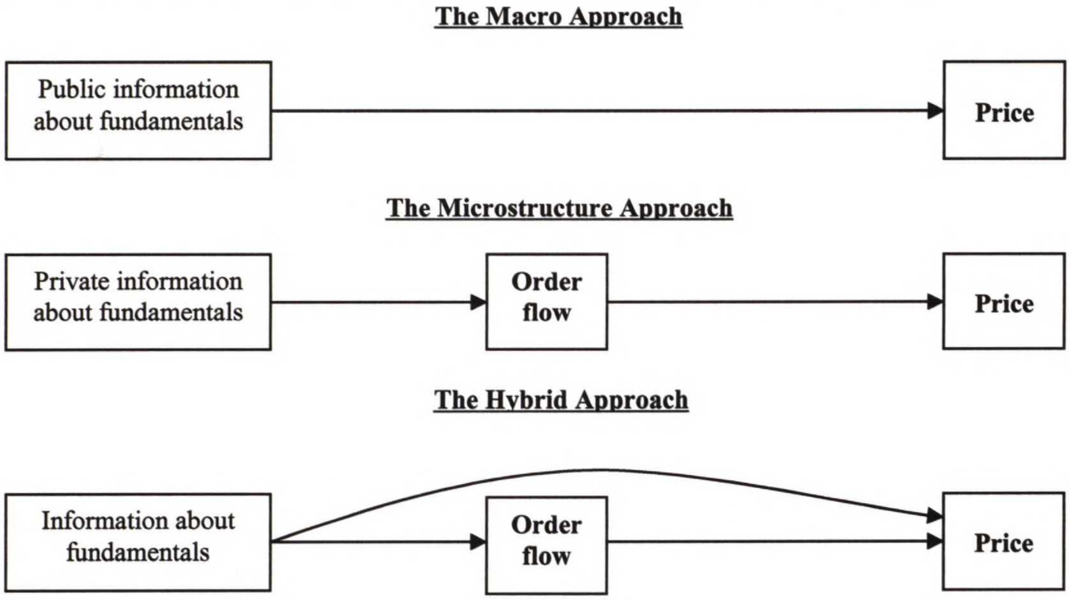
Following the studies of Evans and Lyons (2002a) and Bjonnes et al. (2005), I investigate an equation with components from both the macroeconomic and microstructure models to establish a link between both the macro approach and the microstructure:

$$\Delta P_t = g(\Delta I, \Delta X, \ldots) + f(\Delta i, \Delta m, \Delta g, \ldots) + \varepsilon_{t,} \qquad (4)$$

where the macro component of the model is presented by the function $f(\Delta i, \Delta m, \Delta g, \ldots)$ and the micro component is presented by the function $g(\Delta I, \Delta X, \ldots)$. To be able to estimate ΔP_t in this model, the frequency must be set according to the asset approach by using time-aggregated measures of order flow. Importantly, what needs to be kept in mind is that the values of $g(\Delta I, \Delta X, \ldots)$ and $f(\Delta i, \Delta m, \Delta g, \ldots)$ depend on more than just the past and present values of their determinants – essentially, they also depend on the expectations of their future values. The rational foreign exchange markets are forward looking, which makes these expectations of future values important for setting the foreign exchange rates today.

A graphical presentation below shows clearly the difference between the macro approach, the microstructure models and the hybrid models and how the information from the fundamentals is transferred to the actual foreign exchange rates. It follows the logic of a similar illustration presented in Lyons (2001). The top panel in Fig. 2 below illustrates the link between fundamentals and foreign exchange rate under the traditional macro approach. The fundamental information is publicly known as well as the mapping from that information to the foreign exchange rates. Therefore, price adjustments are instantaneous and direct. The middle panel in Fig. 2 illustrates the microstructure approach where the focus is on private information about the fundamentals. Here the fundamental information is first transferred into order flow. After observing this information signal the market maker learns the need for rate adjustment. Finally, the hybrid approach is illustrated in the bottom panel of the Fig. 2. The hybrid approach accommodates possibilities from both the macro approach and microstructure: fundamental information that affects foreign exchange rates immediately and directly as well as fundamental information that affects foreign exchange rates through an information carrier, order flow. With this hybrid approach the data determines the relative importance of both the information types.

Figure 2 – Graphical presentation of the different approaches to foreign exchange rates



Graphical illustration of the differences between the macro, microstructure and hybrid approaches. The top panel presents the connection between information and foreign exchange rates under the traditional macro approach: information about fundamentals as well as the mapping to price is public and thus, rate adjustments are instantaneous and direct. The middle panel shows the microstructure approach: information is not public and the exchange rate adjustments are based on the information signals transferred via order flow to market makers. The bottom panel illustrates the hybrid approach which includes both types of information and exchange rate adjustments.

The hybrid approach represents the actual foreign exchange market closely as it does not limit the information type about fundamentals. Furthermore, the hybrid approach allows flexibility about the mapping of fundamental information into foreign exchange rates.

5.4. Theoretical framework of the model

5.4.1. Liquidity

Market makers i.e. the dealers are the liquidity providers of the foreign exchange market. They offer bid and ask quotes to other market makers or customers. The aggressive or active part in a transaction buys at the ask price and sells at the bid price, implying ask price being greater than bid. Microstructure models predict the theoretical positive correlation that a buy initiative increases foreign exchange rates and a sell initiative decreases the rate. This correlation is explained by two main branches: inventory control models such as in Lyons (1995), Yao (1998) and Bjonnes and Rime (2005) and information-based models such as in Evans and Lyons (2002a), Payne (2003) and Bjonnes et al. (2005). According to Bjonnes et al. (2005), the effect of inventory control models is only temporary but the effect of information-based models is permanent. This permanent effect is one key factor why I focus in my thesis in the information-based model. This allows me to forecast foreign exchange rates at different time horizons. Another factor is that my data set does not allow empirical testing of the inventory control models.

Learning and adverse selection problems are considered in the information-based models when some participants of the foreign exchange market have private, non-public information. After receiving a trade, a market maker revises her expectations and sets spreads to protect herself against more informed traders, creating permanent effects. The order flow of the aggressive trader will be positively correlated with contemporaneous price changes according to the microstructure theory. According to Bjonnes et al. (2005), however, flows of liquidity providers are expected to be negatively correlated with contemporaneous price changes.

Usually the market makers do not take large overnight positions as stated by Lyons (1995) and Bjonnes and Rime (2005). However, these same market makers are the liquidity providers in the foreign exchange market. This suggests that the dealers unload their inventories almost completely to non-bank customers before the end of day. Also, mean reversion in market maker inventories is much faster in the foreign exchange market than in equity markets, according to Bjonnes and Rime (2005), meaning that the half-lives of market maker inventories range from less than one minute to fifteen minutes. Therefore I can hypothesize that some particular group of market participants acts as an overnight liquidity provider.

5.4.2. Intra-day trading

In the real world, trading in the foreign exchange market takes place continuously, 24 hours in a day, seven days a week.[7] Market makers receive customer orders and trade with each other throughout the trading day. Executing customer orders creates positions to the market makers and some market makers want to close these positions immediately while others speculate on intra-day rate movements. Customer trades are executed with a wider bid/ask spread than trades between market makers, meaning that market makers earn on the bid/ask spread when

[7] Although trading activity during weekends is minimal (Evans and Lyons, 2002).

closing their customer created positions. Market makers adjust their prices if there is excess supply or demand for a particular currency for that means that market makers as a whole are not keen to keep the net position of that particular currency. After this price adjustment by the market makers, non-bank customers absorb some of that excess supply or demand of a particular currency as they find the adjusted price attractive and thus place orders. This continuous price adjustment will finally reach such a level that the market makers as a whole are willing to hold their net positions overnight. This equilibrium price may indeed be on a level where the market makers as a whole do not have any net position and the excess supply or demand has been entirely absorbed by the non-bank customers.

5.4.3. Portfolio shifts model

I will base the empirical part of my thesis on the portfolio shifts model of Evans and Lyons (2002a). It is imperative to understand that their model replicates the above description of the foreign exchange market trading in a conventional manner.

Portfolio shifts on the part of the non-bank customers is one source of foreign exchange rate movements in the model, according to Evans and Lyons (2001). In addition, these portfolio shifts have two important features. First, they are not publicly observed as they occur. Second, they are large enough that adjustment of the spot rate is required to clear the market. This first feature provides a role for order flow. To describe the model shortly, portfolio shifts of the customers are noted in foreign exchange orders at the beginning of each day. These initial shifts are private information. Market makers are on the other side of these orders and during the day, trade among each other to share the resulting inventory risk. The market learns this private information by observing this interdealer activity through brokers. At the end of the trading day, the inventory risk of market makers is shared with the customers.

According to Evans and Lyons (2001), the second feature of the public portfolio shifts - that they are large enough to move exchange rates - requires that the public's demand for foreign-currency assets is not perfectly elastic. If this requirement is filled, different-currency assets are not perfect substitutes and to clear the market, price adjustments are required. Evans and Lyons (2005) study whether different-currency assets are imperfect substitutes and they find it strongly supported, with evidence from both temporary and persistent effects. As asset supply

- the driving force in portfolio balance models - is constant in the Evans and Lyons (2002a) model, their model identifies two distinct components on the demand side: innovations in public information (macro fundamentals) and portfolio shifts (which is private information).

5.4.4. Trading round 1

The Evans and Lyons (2002a) model incorporates three trading rounds every day. Before making their initial quotes in round 1, all individual market makers *i* observe public information increment Δr_t ($R = \sum_{t=1}^{T} \Delta r_t$). These information increments are normally distributed i.i.d., Normal($0, \sigma_r^2$) and represent information flow of public macro events. To concretize these abstract information increments, they can be thought of as changes in interest rates. When the initial quotes are made in round 1 (Round 1 price of dealer *i*, $P_{i1} = P_1$ as all market makers have the same public information), each of the N market makers receives customer orders from her own customers that aggregates into $c_1 = \sum_{i=1}^{N} c_{i1}$, where $c_1 < 0$ indicates a net customer sale. These orders are private information, the portfolio shifts, as they are not observed by other market makers. Furthermore, they are normally distributed and uncorrelated across dealers.

5.4.5. Trading round 2

The interdealer trading starts at round 2. Again, all market makers quote a scalar price to other market makers in the start of round 2 (they do not want to reveal their private information, and thus $P_{i2} = P_2$). Now, during round 2 they trade among themselves to speculate on their private information and to share their inventory risk from their customer trades of round 1. Finally, at the close of round 2, all market makers detect the net interdealer order flow Δx ($\Delta x = \sum_{i=1}^{N} T_{i2}$). This information about the interdealer order flow is imperative as it conveys the size and sign of the public order flow in round 1. Net interdealer transactions T_{i2} commenced by market maker *i* are proportional to her customer orders in round 1, implying that when market makers observe the interdealer order flow *x* from the brokers, they can infer the aggregate public order flow c_1 from round 1 ($\Delta x = \sum_i T_i = \alpha C$, where α is a constant coefficient). Thus, the customer trading in round 1 is mirrored by the order flows in the interdealer trading.

5.4.6. Trading round 3

The mass of customers is largely relative to the mass of N market makers, implying that the market makers' ability for bearing overnight risk is small compared to the customers' ability. Furthermore, according to Lyons (1995) and Yao (1998), it is common practice for foreign exchange market makers to close each trading day with zero net position. Therefore, in the final round 3, it is in the best interest of the market makers to set such prices that the non-bank customers willingly absorb all market maker imbalances and the market makers use information on net interdealer order flow x in round 2 to accomplish this.

Unlike round 1, the customers' motive for trading in round 3 is purely speculative. To set the appropriate prices of round 3, market makers need to know (1) the total flow that the customers need to absorb and (2) the customers' risk-bearing capacity (assumed less than infinite i.e. foreign- and domestic-currency assets are imperfect substitutes). Market makers learn the total flow by observing Δx (as noted, $\Delta x = \alpha C$). The assumption that foreign- and domestic-currency assets are not perfect substitutes is a key assumption in the model: it allows for portfolio balance effects on prices in the model. Finally, the round 3 total demand for foreign exchange of the public, denoted c_3, is a linear function of its expected return conditional on public information:

$$C_3 = \gamma\left(E\left[P_{t+1}^3 + R_{t+1} \middle| \Omega_3\right] - P_t^3\right) \tag{5}$$

Here, the aggregate risk-bearing capacity of the public is captured by the positive coefficient γ. The larger γ, the larger foreign exchange position is willingly absorbed by the public for a given expected return. Ω_3 is the available public information at round 3, including all past ΔR_t and Δx_t.

5.4.7. Equilibrium for interdealer order flow

As noted above, all market makers quote a common scalar price in all the three trading rounds (necessary for no arbitrage). This price is thus conditioned on public information only. Furthermore, even though each day's information increment Δr_t is public information at the beginning of round 1, interdealer order flow Δx_t is not observed until the end of round 2. Moreover, the foreign exchange price for trading in round 3, P_3 reflects the information in both Δr_t and Δx_t.

The Appendix F presents the full mathematical solution to this model. The following part gives a short reasoning of the solution of the model. To understand why the information in the order flow Δx_t relates to portfolio balance effect, note that in equilibrium each market maker's interdealer transaction, T_{i2}, will be proportional to the customer order C_{i1} she received in round 1. This implies that when market makers note Δx_t at the end of round 2, they can learn the aggregate portfolio shift on the part of the public in round 1, $\sum_{i=1}^{N} c_{i1}$. Moreover, the market makers recognize that, for risk-averse public to absorb this portfolio shift in round 3, the foreign exchange rate must be adjusted. More precisely, the rate adjusts in round 3 so that $C_1 + C_3 = 0$, where C_3 is given by Eq. (5) (leaving market makers without overnight net position). Therefore, the rate at the end of day t is:

$$P_t = \beta_1 \sum_{\tau=1}^{t} \Delta R_\tau + \beta_2 \sum_{\tau=1}^{t} \Delta X_\tau \tag{6}$$

and thus, the resulting change in the foreign exchange rate from the end of period t-1 to the end of period t can be written as:

$$\Delta P_t = \beta_1 \Delta R_t + \beta_2 \Delta X_t, \tag{7}$$

where β_2 is a positive constant depending on both γ and α.

The above theory suggests why the theoretical correlation between order flow and foreign exchange rate is positive: if cumulative x_t is negative, this implies that cumulative c_1 is also negative, which is an increase in net supply. And this in turn, requires a decrease in rates to clear the market. Again, the variable that conveys this information about the decrease in net supply is x_t, while c_1 is unobservable. P_t, on the other hand, depends on the sum of the x_t as each additional decrease in c_1 requires a persistent incremental increase in rates.

5.4.8. Equilibrium for customer order flow

As an example of the round 3 quoting, if market makers are long in euros, they must reduce the price for euros to persuade customers to buy euros. Therefore, the quoted price of round 3 is

$$P_{i3} = P_3 = P_2 + \beta x, \tag{8}$$

where β is a constant depending on the market makers trading strategy and on the customers' demand.

To create the equilibrium, think of the following example. If customers (on an aggregate net level) buy euros in round 1, the aggregate interdealer order flow Δx observed at the end of round 2 will be positive as market makers are buying back the euros they sold to customers. Since market makers unload their positions during the final round 3, it means that aggregate customer orders in rounds 1 and 3 need to be of similar size and with opposite sign. Thus,

$$c_1 = \frac{1}{\alpha} x = -c_3 . \tag{9}$$

Finally, the above theory implies that the rate at the end of day t is:

$$P_t = \beta_1 \sum_{\tau=1}^{t} \Delta R_\tau + \beta_2 \sum_{\tau=1}^{t} \Delta c_\tau \tag{10}$$

and similarly than in Eq. (7), the resulting change in the rate from the end of period t-1 to the end of period t can be written as:

$$\Delta P_t = \beta_1 \Delta R_t + \beta_2 \Delta c_t , \tag{11}$$

where c is the customer order flow.

Evans and Lyons (2002a) use data on overnight deposit rates and order flows from the interdealer market to test their model. They demonstrate that the interdealer order flows explain a large proportion of the daily variations in foreign exchange rates (JPY/USD and DEM/USD). Evans and Lyons (2002a) are not able to examine the rounds 1 and 3 directly as they do not have customer order flow data. In contrast, Bjonnes et al. (2005) use the same model to study these initial and final rounds. They speculate that if the typical round 1 customer is different from the typical round 3 customer, they may say that different types of customers fill different roles. Moreover, they state that the customers of round 1 are the active ones because they are first and responsible for the market makers' inventory imbalances. And finally, customers of round 3 are passive as they absorb the market makers' imbalances.

Furthermore, Bjonnes et al. (2005) propose a different mindset as an alternative to the first round-third round framework. They state that the different customers can be thought as either pushing the market or being pulled by the market.[8] The foreign exchange rate rises or falls are initiated by the push customers through the net of their buy or sell orders, thus creating positive correlation between their trading and foreign exchange rate movements. In the contrary, pull customers are attracted into the market by attractive rates which suit them as they wish to trade on a certain side of the market. Moreover, according to Bjonnes et al. (2005), the pull customers decide to act immediately rather than delay the trade hoping for a better price. This creates negative correlation between their trading and foreign exchange rate movements.

5.5. Causality

In the canonical models (Glosten and Milgrom, 1985; Kyle, 1985; Stoll, 1978; and Amihud and Mendelson, 1980) price innovations are a function of order flow innovations i.e. order flow is a proximate cause of price innovations. Non-public information (i.e. micro-level

[8] The terms "push" and "pull" customers were suggested by Professor Mark P. Taylor for Bjonnes et al. (2005).

information about uncertain demands, payoffs, outputs, risk preferences etc.) is the underlying driver of order flow and thus, the underlying dispersed information is the primitive cause of price innovations. Order flow is simply a channel through which the underlying information passes into foreign exchange prices. Empirically order flow appears to act as a kind of expectation proxy. It imitates individuals' expectations about future macro variables, including an ability to forecast those variables. However, when this is the case, alternative hypotheses of reverse causality do exist. The following part identifies these specific alternatives of reverse causality for judgment.

Three possibilities, under which causality is reversed, do exist due to the timing of the order flow-price relation, depending on whether order flow precedes, is contemporaneous with, or lags foreign exchange rate movements. Like Evans and Lyons (2001), I refer to these as the Anticipation hypothesis, the Pressure hypothesis, and the Feedback hypothesis, respectively.

Also variations of these three timing hypotheses exist, according to Evans and Lyons (2001). As the foreign exchange market has low transparency, order flow is not generally observed by market participants when it takes place. This enables, under the Anticipation hypothesis, that order flow can precede rate movements as rates adjust fully only after order flow is commonly surveyed by market makers. Also, because foreign exchange rates may move only after some piece of news anticipated by order flow is commonly surveyed, order flow may precede price movements. Feedback trading causes order flow to lag foreign exchange rate movements under the Feedback hypothesis. This feedback trading can either be negative (i.e. systematic selling in response to rate increases, and buying in response to rate decreases) or positive (i.e. opposite to negative feedback trading).

Despite their contemporaneous realization, the direction of causality is from order flow to price under the Pressure hypothesis. However, this does not rule out the fact that price cannot affect order flow and in microstructure models it affects order flow. Nevertheless, in equilibrium foreign exchange rate movements are functions of order flow innovation and not vice versa. According to Evans and Lyons (2001), this is also the case under most variations of the Anticipation hypothesis. For example, order flow could affect price with a delay under the abovementioned variation where order flow is not generally surveyed by market participants.

The direction of causality becomes a problem under the Feedback hypothesis, in which the direction is reversed i.e. from price to order flow.[9] In negative feedback trading, one would expect a negative order flow-price relation and in positive feedback trading, one would expect order flow in period t to be positively related to the price change in period $t-1$. If this is the case, order flow coefficient in period t would catch the effect of feedback trading and, including a lagged price change, should weaken the significance of order flow coefficient.

5.6. The hypotheses

The Evans-Lyons model presented in the groundbreaking study of Evans and Lyons (2002a) provided justification for the reason why the cumulative interdealer, or market maker order flow follows a random walk, whereas at the same time individual dealers do not have any overnight positions. According to Evans and Lyons (2002a), the aggregate dealer position is completely absorbed by the public, or end-customers at the end of each day and this fact explains the random walk of the cumulative market maker order flow. This absorption of the positions can be called a market-clearing mechanism and it has great implications for total customer flow, according to Lyons (2001). Furthermore, it implies, for example, that:

Hypothesis 1: Marketwide, customer order flow should net to zero every day.

The results of the model of Evans and Lyons (2002a) state that dealers do not want to have any positions overnight. This is a consequence of the assumption that the market makers' risk capacity to bear risk is rather small relative to the risk-bearing capacity of the public i.e. all non-dealer market participants together. The problem with the Hypothesis 1, however, is that without the customer order flow data from all the banks this hypothesis is not testable. Even if the portfolio shifts model was literally true, one would not expect the customer order flow to net to zero every day due to this data problem. Therefore, I cannot empirically test the Hypothesis 1. One could, however, state that my data set, which is from a single bank, represents a random sample, for example 5% to 35% depending on the market, of the marketwide, global customer order flow. If this is the case, then according to Lyons (2001), the Evans and Lyons (2002a) model predicts that:

[9] Note that this does not imply that the direction of causality is fully reversed. The Feedback hypothesis does not rule out feedback trading affecting foreign exchange rates.

Hypothesis 2: For a single bank, customer order flow each day should differ from zero only due to random sampling error.

Hypothesis 3: For a single bank, customer order flow each day should be uncorrelated with changes in the exchange rate.

Here the customer-order sample is assumed to be random and the Hypothesis 3 follows from this assumption. Theoretically the sample should contain, on average, as many occurrences of the "shock" orders in the beginning of each day as it does contain the "absorption" orders at the end of each day (the models C_1's and C_3's, respectively).

One possibility, however, is that the customer orders of different customer types do not convey equal information of subsequent market rate movements and their market impacts are not alike. Therefore, the customers could be divided into two categories as Lyons (2001) does: high-impact customers and low-impact customers. This division into categories implies that the customer order sample may not represent the customer order population as the bank could have unusually high or low share of high-impact customers. This implies the next hypothesis:

Hypothesis 4: Different customer types have similar market impacts.

A variation of the Anticipation hypothesis, in which order flow is not generally surveyed by market participants, implies that order flow could affect foreign exchange rates with a delay. I am able to examine this variation by introducing lagged order flow component to the hybrid model. If this lagged order flow component is found significant, it means order flow affects foreign exchange rates with a delay. If it is insignificant, I can state that the lagged order flow is already embedded in the foreign exchange rate. This implies the following hypothesis:

Hypothesis 5: Lagged order flow affects price movements under the Anticipation hypothesis.

The assumptions of the Feedback hypothesis enable that the direction of causality goes in reverse i.e. from price to order flow. The feedback trading of the Feedback hypothesis can be either negative or positive. In a presence of positive feedback trading one would expect order flow in period *t* to be positively related to the price change in period *t-1* and vice versa for negative feedback trading. I can examine this hypothesis by including a lagged price component to the hybrid model. If positive or negative feedback trading exists in my data sample, the significance of order flow should be weakened or eliminated by the inclusion of a lagged price component. This implies the following hypothesis:

Hypothesis 6: Lagged price movements reduce the significance of order flow in period *t*.

The next Section 6 continues by describing the data set I use in this thesis.

6. The data set

The data set used in this thesis consists of all DKK/EUR, NOK/EUR, SEK/EUR and USD/EUR FX-Spot and FX-Outright transactions of a leading Nordic bank during a period from September 18, 2002 to February 28, 2008. The whole data period therefore consist of more than 1.4 million foreign exchange transactions. Table 3 below presents the global average daily turnover of DKK/EUR, NOK/EUR, SEK/EUR and USD/EUR foreign exchange markets (spot and forward transactions) in billion dollars in April 2007 and the market shares of my data set during that period.

Table 3 – Daily turnover of foreign exchange markets (spot and forward transactions) and market shares

	DKK/EUR	NOK/EUR	SEK/EUR	USD/EUR
Daily turnover (in billion dollars)	3.5	2.4	13.1	355.6
Data set market share	20-25 %	30-35 %	5-10 %	< 1 %

This table presents the average daily turnover of different foreign exchange markets for spot and forward transactions in April 2007 (in billion dollars) and the market share of the data set during that period. Daily turnovers are from Danmarks Nationalbank (2007), Norges Bank (2008) [Adjusted, based on Meyer and Skjelvik (2006)] and from BIS (2007). Data set market shares have been calculated as follows: Average daily turnover in euros (the turnover of each single transaction was converted to euros with prevailing market prices during the exact time of the deal) in April 2007 converted to dollars with average USD/EUR rate in April 2007 divided by the respective daily turnover.

The total number of trades is over 1.4 million, which is somewhat considerable for a study such as this. More importantly, to my knowledge, only USD/EUR and SEK/EUR markets of my data set have been studied in the existing academic literature[10]. Furthermore, my data set has significant market shares of the two non-studied foreign exchange markets, DKK/EUR and NOK/EUR.

According to Lyons (2001), the foreign exchange market data sets can be divided into three different basic types: customer-dealer trades, direct interdealer trades and brokered interdealer trades, each with roughly one third of the total trading. The share of non-financial customers of the total reported foreign exchange market turnover in April 2007 was 17% while the share of turnover traded with other reporting dealers was 43%, according to BIS (2007). My data set does not allow for differentiating between direct interdealer and brokered interdealer trades but allows for differentiating between customer-dealer and interdealer trades. Table 4 below presents the number of deals per currency pair with interdealer-customer trading split.

Table 4 – Number of deals per currency pair with interdealer-customer trading split

	Market maker	(%)	Other	(%)	Total
DKK/EUR	58,000	51 %	56,000	49 %	114,000
NOK/EUR	177,000	59 %	124,000	41 %	301,000
SEK/EUR	144,000	44 %	185,000	56 %	329,000
USD/EUR	499,000	75 %	168,000	25 %	667,000
Total	878,000	62 %	533,000	38 %	1,411,000

The above table presents the number of deals in the data set per currency pair with interdealer-customer trading split, both in absolute and relative number of deals. The data period spans from September 18, 2002 to February 28, 2008.

As the Table 4 shows, the proportion of customer-dealer trades is roughly one third on a total level (although for the Nordic currencies the split is more close to 50-50). Therefore, the data set I use has substantial customer trading included, which is considered extremely positive when conducting this kind of a study. The most interesting feature in my data set is that it includes over half a million customer-dealer transactions. Previously the academic literature about market microstructure in the foreign exchange market has used only two available data sets (to my best knowledge): the data set of Fan and Lyons (2000), which is obtained from Citibank covering a sample period of seven years and the data set of Bjonnes et al. (2005),

[10] The NOK/EUR market has been very briefly studied by the central bank of Norway (Rime and Sojli, 2006).

obtained from the Swedish central bank, Riksbank. The data set of Bjonnes et al. (2005) covers 10 years of trading with over 90% of all global worldwide SEK/EUR transactions.

Furthermore, the data set of Bjonnes et al. (2005) allows them to distinguish between financial and non-financial customers as well as interdealer and central bank trading. Fan and Lyons (2000) are able to distinguish between leveraged and unleveraged financial customers as well as non-financial corporate customers. My data set, however, allows me to differentiate the customer-dealer trading into seven different customer types: central bank, corporate, credit institution, market maker, insurance company, public institution and state owned company. Table 5 below reports the number of transactions per customer type and currency pair as well as their relative share of the total number of transactions in my data set.

Table 5 – Number of deals, split by customer type and currency pair (in thousands)

	Central bank	Corporate	Credit institution	Market maker	Insurance company	Public institution	State owned	Total
DKK/EUR	0.2 (0.2)	46 (40.5)	6 (5.3)	58 (50.7)	3 (2.5)	0.4 (0.3)	0.5 (0.5)	114.2
NOK/EUR	0.4 (0.1)	88 (29.3)	26 (8.7)	177 (58.9)	5 (1.8)	4 (1.3)	0 (0.0)	300.8
SEK/EUR	0.6 (0.2)	159 (48.4)	21 (6.3)	144 (43.9)	1 (0.4)	1 (0.4)	1 (0.4)	329.3
USD/EUR	1.5 (0.2)	111 (16.6)	51 (7.6)	499 (74.8)	3 (0.5)	1 (0.2)	0.6 (0.1)	666.3
Total	2.7 (0.2)	404.5 (28.7)	103.5 (7.3)	878.0 (62.2)	12.8 (0.9)	6.6 (0.5)	2.6 (0.2)	1,410.6

The above table reports the absolute number (relative figures in parenthesis) of deals split by customer type and currency pair (in thousands). The reporting period spans from September 18, 2002 to February 28, 2008.

Even though the transactions of corporate customers and market maker customer make up the majority of the data set, to my best knowledge no one in the existing academic literature has been able to differentiate between different customer types so specifically. Furthermore, my data set includes the country of origin of each single customer, allowing me to analyse the effect of nationality in the regressions.

The short (3 month) and long (10 year) interest rate data is gathered from the Swedish central bank (Sveriges Riksbank), Euribor and Board of Governors of the Federal Reserve System

(The Federal Reserve) in early March, 2008. For short term interest rate the daily 3-month Euribor is used for the euro market, 3-month STIBOR for the Swedish market, 3-month CIBOR for the Danish market, 3-month NIBOR for the Norwegian market and 3-month euro-dollar deposit rate for the US dollar market. 10-year government bond yields are used to measure the long term interest rate (for the euro market, the 10-year euro-area bond yield is used). The foreign exchange rate data is downloaded from Bloomberg. In the foreign exchange rate data, each day's closing bid price is used in this thesis.

Due to the fact that weekend trading is minimal, any foreign exchange trading during Saturdays and Sundays is excluded from the data set. As this study is made on four different foreign exchange markets with different holiday calendars, the trading days during the sample period include every weekday regardless of banking holidays. Any gaps in the short or long term interest rate data or in the foreign exchange rate data have been filled with the value of the previous entry. Any gaps in the foreign exchange transaction data have been filled with zero value (i.e. assuming no trading during that day). After careful analysis of the transaction volumes of different customer types in different foreign exchange markets in the Appendix A, the earliest months of the data period are excluded to enhance the validity and quality of the data. Therefore, the final data periods span from October 31, 2003 to February 28, 2008 for DKK/EUR and USD/EUR data, from May 23, 2003 to February 28, 2008 for NOK/EUR data and from May 24, 2004 to February 28, 2008 for SEK/EUR data. This leaves 1,130 banking days for analysis in DKK/EUR and USD/EUR data, 1,245 banking days in NOK/EUR data and 984 banking days in SEK/EUR data.

Most of the graphs of the data set in the Appendix E already show some evidence that the cumulative order flow correlates with the exchange rate, either positively or negatively. For instance, the cumulative order flow of corporate customers seems to correlate negatively with the NOK/EUR foreign exchange rate in Fig. 9, panel C. This, as well as all the other cumulative order flows, will be econometrically verified in the regressions later in the Section 7.

6.1. Distribution of the cumulative order flow positions

The following four tables present some descriptive statistics, such as mean and standard deviation of the cumulative order flow positions, for the different customer types and currency pairs at the 1-day horizon.

Table 6 – Descriptive statistics of the cum. order flow series for different customer groups (DKK/EUR)

	Central bank	Corporate	Credit institution	Insurance company	Market maker	Public institution	State owned
Mean	-271.12	-653.41	-74.91	-254.32	1576.67	102.72	43.63
Std. dev.	138.70	408.05	85.40	285.27	1069.93	29.85	19.19
Skewness	0.15	-0.27	-0.88	-0.22	0.23	-2.33	-0.61
Kurtosis	1.61	1.96	2.31	1.38	1.60	7.76	2.43

The above table presents the mean, standard deviation, skewness and kurtosis for all the different customer types for DKK/EUR. The sample period spans from October 31, 2003 to February 28, 2008. All positions are measured in EUR 10 million.

Table 7 – Descriptive statistics of the cum. order flow series for different customer groups (NOK/EUR)

	Central bank	Corporate	Credit institution	Insurance company	Market maker	Public institution	State owned
Mean	107.48	-204.25	-81.13	-54.26	44.99	-72.38	0.08
Std. dev.	63.62	110.00	76.96	17.39	118.79	61.13	0.15
Skewness	-0.94	-0.66	-1.17	1.12	-0.17	-0.45	-0.27
Kurtosis	2.00	3.07	3.97	5.29	2.17	1.80	1.29

This table presents the mean, standard deviation, skewness and kurtosis for all the different customer types for NOK/EUR. The sample period spans from May 23, 2003 to February 28, 2008. All positions are measured in EUR 10 million.

Table 8 – Descriptive statistics of the cum. order flow series for different customer groups (SEK/EUR)

	Central bank	Corporate	Credit institution	Insurance company	Market maker	Public institution	State owned
Mean	28.72	-391.44	-104.93	-38.95	3.78	-19.30	50.01
Std. dev.	26.19	244.05	89.72	25.08	49.72	22.11	39.24
Skewness	0.25	-0.04	-0.31	-0.23	-0.03	-0.45	0.72
Kurtosis	1.67	2.18	1.48	2.27	2.65	2.69	2.49

This table presents the mean, standard deviation, skewness and kurtosis for all the different customer types for SEK/EUR. The sample period spans from May 24, 2004 to February 28, 2008. All positions are measured in EUR 10 million.

Table 9 – Descriptive statistics of the cum. order flow series for different customer groups (USD/EUR)

	Central bank	Corporate	Credit institution	Insurance company	Market maker	Public institution	State owned
Mean	-30.47	58.17	41.29	66.61	263.70	26.54	-27.79
Std. dev.	44.66	37.06	60.66	60.05	247.79	16.18	15.81
Skewness	-0.61	0.87	0.55	0.17	0.39	-0.31	0.28
Kurtosis	2.72	3.66	2.61	1.44	1.73	2.58	1.99

The above table presents the mean, standard deviation, skewness and kurtosis for all the different customer types for USD/EUR. The sample period spans from October 31, 2003 to February 28, 2008. All positions are measured in EUR 10 million.

None of the cumulative order flow series of any customer type or currency pair is normally distributed with the exception of market maker order flow of the SEK/EUR market. Based on the Jarque-Bera test statistic the null hypothesis of normal distribution cannot be rejected at the 5% confidence level for market maker order flow of the SEK/EUR market. For all other order flow positions the null hypothesis of normal distribution can be rejected at the 1% confidence level.

6.2. Nonstationarity

A general problem with time series data is that the independent variables may seem to be more significant than they actually are if they have the same trend as the dependent variable. This problem causes the regressions to be spurious and the Student's t-statistics and the overall fit of the regression are overstated. Here the problem may be caused by nonstationary time series and a test of stationarity is needed first. The following Table 10 presents the results of the formal test of stationarity, the unit root test for all studied markets.

Table 10 – Results of the augmented Dickey-Fuller unit root tests

		Exchange rate	Corporate	State owned company	Public institution	Central bank	Market maker	Credit institution	Insurance company	Dif 10y	Dif 3m
DKK/EUR	Level	11.8 %	99.9 %	15.2 %	0 %	55.6 %	96.3 %	92.9 %	81.1 %	34.7 %	11.6 %
	1st diff.	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
NOK/EUR	Level	14.2 %	27.5 %	78.9 %	100 %	42.2 %	53.1 %	100 %	55.6 %	0.2 %	0.5 %
	1st diff.	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
SEK/EUR	Level	5.4 %	99.6 %	100 %	90.1 %	87.9 %	8.3 %	99.0 %	48.6 %	23.3 %	92.6 %
	1st diff.	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
USD/EUR	Level	91.6 %	0.3 %	86.6 %	92.4 %	75.4 %	95.3 %	97.5 %	92.4 %	86.2 %	86.7 %
	1st diff.	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %

The above table reports the results of the augmented Dickey-Fuller unit root tests for the exchange rate, different customer types and short and long term interest rate differentials. The table is divided into four panels representing each studied market. The first and second row of each panel reports the associated one-sided *p*-values in the level and in the first difference of the different series, respectively.

As we can see from the results, the null hypothesis of unit root cannot be rejected in most of the cases. Only the position of public institutions in the DKK/EUR market, corporate customers in the USD/EUR market and the interest rate differentials in the NOK/EUR market are not I(1) (i.e. they can be transformed into a stationary process by differencing once and can be described as integrated of order 1) at the 1% confidence level and are therefore stationary.[11] For the SEK/EUR exchange rate and the position of market maker in the SEK/EUR market, however, the null of unit root can be rejected at the 10% confidence level.

According to Bjonnes et al. (2005), the interest rate differentials are usually considered to be stationary. In my data set, this seems to be the case only in the NOK/EUR market. All the exchange rate series seem to have a unit root and are I(1) at the 5% confidence level.

Dougherty (2007) notes that the augmented Dickey-Fuller (ADF) test tends to have low power. For the ADF test, it is often impossible to distinguish an autocorrelated stationary autoregressive process from a nonstationary process. Therefore, I have run various other tests for the groups consisting of all the above series in all markets. The results are presented below.

[11] However, other tests like Elliott-Rothenberg-Stock Dickey-Fuller test with GLS detrending, Elliott-Rothenberg-Stock Point-Optimal test and Ng-Perron test fail to reject the null hypothesis of unit root on these four series at the 5% level. The question of unit root therefore remains unanswered for them.

Table 11 – Results of the unit root tests in the level for different markets

Method	DKK/EUR	NOK/EUR	SEK/EUR	USD/EUR
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t-stat	70.5 %	97.2 %	100 %	89.9 %
Breitung t-stat	85.1 %	96.0 %	52.8 %	96.0 %
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	55.3 %	78.4 %	100 %	99.8 %
ADF - Fisher Chi-square	2.7 %	2.6 %	72.7 %	85.5 %
ADF - Choi Z-stat	49.5 %	69.6 %	99.9 %	99.8 %
PP - Fisher Chi-square	3.9 %	1.7 %	55.3 %	88.5 %
PP - Choi Z-stat	45.9 %	50.8 %	99.4 %	99.9 %
Null: No unit root (assumes common unit root process)				
Hadri Z-stat	0 %	0 %	0 %	0 %

The above table presents the associated *p*-values of various unit root tests in the level of the group of all different series (exchange rate, customer types and interest rate differentials). Probabilities for the Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

When the tests in Table 11 are run in the first difference for the groups in all markets, all *p*-values are 0% (except for the Hadri Z-stat test, where the null hypothesis assumes no unit root. Those *p*-values indicate rejection of the null). Therefore, when looked upon as a group, only the ADF and the Phillips-Perron (PP) tests indicate that the group of different series in the DKK/EUR and NOK/EUR markets are not I(1) when using the Fisher Chi-square distribution. With Choi Z-stat, also these two tests indicate unit roots in these markets.

7. Empirical results

Cornell (1977), Mussa (1979) and Frenkel (1981) all note that foreign exchange rate changes are largely unpredictable. Furthermore, Mussa states that: "The natural logarithm of the spot exchange rate follows approximately a random walk". What the results of the study by Meese and Rogoff (1983a) support and what Mussa also points out, is that any serial correlation found in the foreign exchange rates by in-sample tests is likely to be unstable over time. The following results as well as the previous academic literature in microstructure indicate that these statements are false.

The unit root tests in the Section 6.3 indicate that a majority of the different series are I(1) i.e. they can be described as integrated of order 1 and thus are nonstationary. More importantly, all the exchange rate series are I(1). According to Studenmund (2006), spurious regressions can be avoided if the variables are cointegrated, even though the dependent variable (the exchange rates) and at least one independent variable (cumulative order flows) are nonstationary. Therefore, I have cointegrated the series in the next Section 7.1.

7.1. Cointegration

Studenmund (2006) states that even though the unit root tests performed in the Section 6.2 revealed nonstationarity, using differences in the regressions makes the regression results valid. Differences should not be used, however, until the residuals have been tested for cointegration.

Cointegration refers to a situation when linear combinations of nonstationary time series are stationary, which suggests the existence of a long-run equilibrium between these variables. In the fully specified regression model $y_t = \beta x_t + \varepsilon_t$, there is a presumption that the disturbances ε_t are a stationary series. However, according to Greene (1997), this is unlikely to be true if y_t and x_t are integrated series (i.e. nonstationary). On the other hand, if both of the series are I(1), there may be a β such that $\varepsilon_t = y_t - \beta x_t$ is I(0). Greene (1997) states, that if the two series are both I(1), this partial difference could have a fixed mean and be stable around it, i.e. the series would be drifting together roughly at the same rate and therefore would be cointegrated.

I have used the Engle-Granger cointegration method, first suggested by Engle and Granger (1987), on daily observations to estimate the cointegration framework. Including a stationary variable may affect the cointegration tests, according to Bjonnes et al. (2005). However, regarding a nonstationary variable as stationary in the cointegration may have implications for the inference. Even though the ADF test indicates that some of the variables are stationary, the additional tests gave rise to nonstationarity in those variables. As a result, I have chosen to treat all variables as nonstationary in the cointegration framework to get the correct inference.

The first step of the Engle-Granger method is to estimate the variables using basic ordinary least squares (OLS) method. Then, the residuals of this first regression are tested for unit root using the ADF method and if the residuals are found stationary, the variables are said to be cointegrated. I have tested for cointegration in the following equation:

$$p_t = \beta_1 + \beta_2 x_{t,i} + \beta_3(i_{10,t} - i^*_{10,t}) + \beta_4(i_{3,t} - i^*_{3,t}) + \beta_5 t, \tag{12}$$

where p_t is the log spot exchange rate at day t, $x_{t,i}$ is the position of customer type i's order flow on day t. $(i_{10,t} - i^*_{10,t})$ is the long-term interest rate differential between the euro area 10-year government bond and the foreign government bond on day t. $(i_{3,t} - i^*_{3,t})$ is the short-term interest rate differential between 3-month Euribor and the foreign equivalent on day t. Finally, t is the linear trend.

The following Table 12 reports the t-statistics of the augmented Dickey-Fuller test of unit root, number of observations in each test and the MacKinnon (1991) critical values for each market.

Table 12 – The results of the ADF unit root test for regression residuals

			MacKinnon (1991) critical values		
Market	ADF test statistic	Obs.	1 %	5 %	10 %
DKK/EUR	-5.104*	1127	-5.263	-4.720	-4.436
NOK/EUR	-5.790**	1244	-5.261	-4.719	-4.435
SEK/EUR	-6.655**	983	-5.267	-4.722	-4.438
USD/EUR	-6.369**	1129	-5.263	-4.720	-4.436

This table reports the augmented Dickey-Fuller (ADF) test statistics for all markets as well as the number of observations in each market and the MacKinnon (1991) critical values at the 1, 5 and 10% level. The null hypothesis of the test is no cointegration in the series. Significance of the test statistics at the 5% (1%) level is represented by * (**).

As the ADF unit root test is performed on the estimated values and not on data series, the test statistic does not follow the conventional Student's t-distribution or the Dickey-Fuller distribution. Engle and Granger (1987) tabulated first the distribution of this test and later MacKinnon (1991) calculated more precise critical values. Therefore, the MacKinnon (1991) critical values are calculated in the above Table 12.

The results of the ADF unit root test indicate clearly that the log spot rate, the order flows of different customer types and the short and long term interest rate differentials are cointegrated as the null hypothesis is rejected at the 1% confidence level (5% level for DKK/EUR market). This means that there is a long-run relation between the foreign exchange rate and cumulative order flow of different customer types as well as interest rate differentials in all the studied markets. Therefore, the Hypothesis 3 can be rejected as customer order flow is correlated with changes in the exchange rate in the long term. This long-term relation allows me to run Engle-Granger error correction model regressions to study short term effects in the next Section 7.2.

7.2. The generalized method of moments (GMM)

I have used the generalized method of moments (GMM) (Hansen, 1982) to execute the error correction regressions of this thesis. The starting point of GMM estimation is a theoretical relation that the parameters should satisfy. The theoretical relation is replaced by its sample counterpart and the estimates are chosen to minimize the weighted distance between the theoretical and actual values. A well suited feature of the GMM estimate is that it does not require information of the exact distribution of the disturbances and therefore it is a robust estimator. The theoretical relations that the parameters should satisfy are usually orthogonality conditions between some function of the parameters and a set of instrumental variables. The GMM estimator selects parameter estimates so that the sample correlations between the instruments and the function are as close to zero as possible.

The following presents the reasoning for using GMM in this thesis. First, unlike the basic OLS method, GMM does not require the usual assumption of normality. As the Section 6.1 illustrates, none of the cumulative order flow positions are normally distributed because of the large number of outliers. The market maker order flow of the SEK/EUR market is an exception, where the null hypothesis of normal distribution cannot be rejected at the 5% confidence level, based on the Jarque-Bera test statistic. Second, the data suffers from conditional heteroskedasticity and serial correlation. Newey and West (1987) show that a weighting matrix used in the generalized method of moments can be adjusted to account for these flaws in the data set. Finally, other empirical microstructure studies have used GMM with positive results (Bessembinder (1994), Madhavan and Smidt (1991), Yao (1998) and Bjonnes et al. (2005), among others).

In all the following regressions, all the regressors are used as a set of instrumental variables, resulting in exactly identified systems and coefficient estimates identical to OLS. Compared to OLS, standard errors are different as they are corrected for conditional heteroskedasticity and autocorrelation following Newey and West (1987). Bartlett kernel type and a fixed bandwidth selection criterion of Newey and West (1987) are used in all regressions. All regressions also include a first-order autoregressive process term, AR(1), to minimize the effect of autocorrelation (not reported in the results). Finally, no prewhitening of the data is used.

7.3. Regression results at the 1-day, 1-month and 3-month horizons

7.3.1. The estimated regression equation

Some changes are made to the Eq. (7) for estimation purposes. First, the dependent variable ΔP_t is changed to the log spot rate, Δp_t. This makes the empirical specification comparable to the previous literature within microstructure theory. Second, the public information increment ΔR_t is replaced with changes in the nominal short and long term interest rates, $\Delta(i_{3,t}-i^*_{3,t})$ and $\Delta(i_{10,t}-i^*_{10,t})$, where $i_{3,t}$ is the 3-month Euribor rate and $i^*_{3,t}$ is the foreign 3-month interest rate (STIBOR, CIBOR, NIBOR or euro-dollar deposit rate) in day *t*. Interest rates are used because they are readily available in daily values, they are the main engine of foreign exchange rate variation in macro models, and this method is also easily comparable to previous literature. Finally, ΔX_t, the order flow is changed to $\Delta x_{t,i}$, which is the order flow of customer type *i*.

With the above changes the estimated regression equation is:

$$\Delta p_t = \beta_1 + \beta_2 \Delta x_{t,i} + \beta_3 \Delta(i_{10,t} - i^*_{10,t}) + \beta_4 \Delta(i_{3,t} - i^*_{3,t}) + \beta_5 t + \beta_6 ECM(-n), \qquad (13)$$

where Δp_t is the change in log spot exchange rate from day *t-n* to day *t* and $\Delta x_{t,i}$ is the change in the order flow of customer type *i* from day *t-n* to day *t*. The regressor $\Delta(i_{10,t} - i^*_{10,t})$ is the change in the long-term interest rate differential between the euro area 10-year government bond and the foreign government bond from day *t-n* to day *t*. The regressor $\Delta(i_{3,t} - i^*_{3,t})$ is the change in the short-term interest rate differential between the 3-month Euribor and its foreign equivalent from day *t-n* to day *t*. Finally, the regressor *t* is the linear trend and ECM(-n) is the error correction term, lagged *n* periods according to the Engle-Granger two-step model (not reported in the results). A linear trend is chosen based on the analysis of the transaction volumes in the Appendix A. The volumes seem to grow linearly instead of exponentially as usual in long time-series data. Running the regressions without the trend component does not affect the results significantly at any time horizon or market. In addition, experiments with other trends than linear did not have any meaningful difference in the coefficients or significances of the regressors. Three different values of *n* are used: 1, 20 and 60 days. These represent the change over a day, a month and three months.[12]

7.3.2. Regression results

The following tables present the results of the regressions. Table 13 is for 1-day, Table 14 for 1-month and Table 15 for 3-month horizon regression results. Even though the NOK/EUR pairwise correlation matrix in the Appendix D gives rise to multicollinearity between corporate customers and other components of the model at the 1-month and 3-month horizons, none of the components is left out of the regression to avoid omitted variables bias in the coefficients. Running the regressions without corporate customer order flow component does not change the results significantly.

Each table is divided into four panels, each representing different foreign exchange markets. The top panel presents DKK/EUR regression results, the second panel NOK/EUR, third panel SEK/EUR and finally the last panel presents the regression results for USD/EUR market. Two figures are presented for each regressor in every panel; the coefficient of the regressor and Student's t-statistic in parenthesis. An asterisk represents statistical significance at the 5% confidence level and two asterisks at the 1% level. The rightmost column reports the R^2 statistics of each regression.

[12] Note that weekends are excluded from the data set so five trading days equal one week. Also, four weeks are considered as a month.

Table 13 – Regression results at the 1-day horizon

	ΔCorp.	ΔState ow. comp.	ΔPublic inst.	ΔCentral bank	ΔMarket maker	ΔCredit inst.	ΔInsur. comp.	Trend	ΔDIF 10Y	ΔDIF 3M	R^2
DKK/EUR	-0.00006	-0.00008	0.00088	-0.00052	-0.00008	0.00002	0.00004	1.39E-09	0.00021	-0.00105	9.01 %
	(-0.593)	(-0.238)	(1.854)	(-3.149)**	(-1.025)	(0.131)	(0.405)	(0.094)	(0.479)	(-0.909)	
NOK/EUR	-0.00681	-0.29153	-0.03295	-0.02169	0.01100	0.02116	-0.00474	1.96E-07	0.00672	0.01533	17.30 %
	(-2.776)**	(-0.246)	(-2.017)*	(-1.633)	(6.699)**	(4.343)**	(-0.866)	(0.745)	(1.981)*	(2.913)**	
SEK/EUR	-0.00367	-0.04781	0.00093	0.00392	0.00640	0.01695	0.01058	2.78E-07	0.00678	0.02013	14.00 %
	(-1.945)	(-2.276)*	(0.206)	(0.908)	(4.679)**	(4.404)**	(3.335)**	(1.114)	(1.681)	(3.604)**	
USD/EUR	0.00542	-0.12797	0.00449	0.00631	0.00479	0.01969	0.01263	-1.43E-07	0.01663	0.00747	7.53 %
	(2.652)**	(-3.857)**	(0.485)	(1.473)	(3.626)**	(4.282)**	(1.737)	(-0.304)	(4.321)**	(1.58)	

Table 13 reports the results for the GMM regression $\Delta p_t = \beta_1 + \beta_2\Delta x_{t,i} + \beta_3\Delta(i_{10,t} - i^*_{10,t}) + \beta_4\Delta(i_{3,t} - i^*_{3,t}) + \beta_5 t + \beta_6 ECM(-n)$, where Δp_t is the change in log spot exchange rate from day *t-n* to day *t* and $\Delta x_{t,i}$ is the change in the order flow of customer type *i* from day *t-n* to day *t*. The regressor $\Delta(i_{10,t} - i^*_{10,t})$ is the change in the long-term interest rate differential between the euro area 10-year government bond and the foreign government bond from day *t-n* to day *t*, here ΔDIF 10Y. The regressor $\Delta(i_{3,t} - i^*_{3,t})$ is the change in the short-term interest rate differential between 3-month Euribor and the foreign equivalent from day *t-n* to day *t*, here ΔDIF 3M. Finally, regressor *t* is the linear trend and ECM(-n) is the error correction term, lagged *n* periods. *n* indicates the different time horizons over which the return is measured, here 1 day. Order flow positions are measured in EUR 1 billion. Estimations are made using daily data and overlapping samples. The sample period spans from October 31, 2003 to February 28, 2008 for DKK/EUR and USD/EUR data, from May 23, 2003 to February 28, 2008 for NOK/EUR data and from May 24, 2004 to February 28, 2008 for SEK/EUR data. Coefficients (all insignificant) and error correction terms are not reported. A single asterisk (*) and two asterisks (**) denote significance at the 5% and 1% level, respectively.

The above results show that in the DKK/EUR market, central banks are the only customer type which has statistically significant effect on the DKK/EUR foreign exchange rate at the 1-day horizon. The coefficient is negative, which means that when central banks buy euros and sell Danish krones, the Danish krone tends to appreciate. This is a surprising result as the Danish central bank accounts for nearly 80% of the total volume in this market and when it sells krones, one might think that krones should depreciate, as stated in the official short-term policy of the Danish central bank. However, central banks from other countries account for slightly over 20% of the total volume in that customer group, causing noise in the data, and the negative coefficient of 0.052% is most likely caused by that reason. Furthermore, the coefficient is rather close to zero so that the effect of central banks' order flow in the DKK/EUR market is somewhat limited. The sign of the coefficient of central banks' order flow stays negative also during the longer horizons with nearly the same values. They are also significant at the 1% confidence level, suggesting that this result is not caused by coincidence. A similar effect can be seen in the NOK/EUR market at the 1-month horizon, where the coefficient of central banks' order flow is -1.7% even though Norway's central bank accounts for 50% of all activity in that group. This finding, however, is not significantly persistent at other studied horizons so no firm conclusions can be drawn.

Neither the short nor long-term interest rate differential plays any role in the DKK/EUR market at the 1-day horizon, contrary to the results of other studied foreign exchange markets. In the NOK/EUR and SEK/EUR markets the short-term interest rate differentials, and in the USD/EUR market the long-term interest rate differential, are significant at the 1% confidence level with positive coefficients. The long-term interest rate differential in the NOK/EUR market is also significant at the 5% level. When the interest rate differential increases the foreign currencies depreciate against euro. The coefficients are of somewhat similar size in these markets except for the long-term in the NOK/EUR market, where it is roughly a third of the other markets.

In the SEK/EUR market, these findings about interest rate differentials differ slightly from the results of Bjonnes et al. (2005), who report that only the long-term interest rate differential is significant at the 1-month and 3-month horizons while short-term differential is not significant. Also, the sizes on the coefficients are different. Bjonnes et al. (2005) report effects of roughly 3% and 0.8% for the long and short term differentials, respectively, at both one and three month horizons. For those horizons my coefficients are 2.0-2.4% and 1.8-2.5% for long and short term differentials, respectively. In the USD/EUR market my findings show an effect of 0.7%, compared to the results of Evans and Lyons (2002), who report 0.5% for the DM/USD market at the 1-day horizon. Although the markets are not quite the same, I believe these results are comparable as the coefficients are of similar size (even though my results are not significant at that horizon for USD/EUR market).

In all the studied markets, excluding the Danish, order flow of other market makers and credit institutions is highly significant with positive coefficients ranging from 0.5% to 1.1% for market makers and from 1.7% to 2.1% for credit institutions, signalling that when these customer types buy euros against foreign currency, euro tends to appreciate and the foreign currency weakens. The main market participants in these two customer types are from the U.S. and the U.K. across the different markets, explaining the similarity of the results across all markets. Otherwise it would have been surprising that the coefficient of the USD/EUR market has the same sign as the other two markets. Moreover, other customer types also have significant coefficients but not so widely. State owned companies have an effect in the SEK/EUR and USD/EUR markets, public institutions in the NOK/EUR market and insurance companies in the SEK/EUR market while corporate customers have significant coefficients in the NOK/EUR and in the USD/EUR markets.

Interestingly, the coefficients of corporate customers' order flow have different signs, although around similar size, in the NOK/EUR and USD/EUR markets. This is explained by the origin of corporate customers, Norway. Norwegian customers make up more than 60% of the total volume in both of these markets in my data set. If the customers of the USD/EUR market would have been from the United States, one could argue that their coefficient should have also been negative. Also the mean of corporate order flow is negative in the NOK/EUR market and positive in the USD/EUR market (see Table 7 and Table 9 in the Section 6.1, respectively), meaning that the same customers tend to buy euros against dollars, depreciating dollar and sell euros against Norwegian krones, depreciating krone.

The coefficient of corporate customers in the NOK/EUR market is negative as these customers tend to sell more euros than buy euros. Presumably their business is conducted in euros in a bigger share than in Norwegian krones and therefore the corporate customers need to exchange their receivables into krones. Then why is the coefficient of corporate customers positive in the USD/EUR market? The answer lies within the country of origin of these customers. The three top countries of corporate customers make up together nearly 90% of all the activity in the USD/EUR market (see panel D of Appendix B) and are all from the Nordic region instead of being from the United States. Allegedly they conduct more business in dollars than euros or prefer to hold euro nominated positions over dollar positions. Therefore, on average they sell more dollars than euros and the coefficient of their order flow is positive. Although the sign of the coefficient is different than in the other markets, the reasoning is exactly the same for the USD/EUR market.

To my best knowledge, this study is the first to take account the country of origin of the customers. Although Bjonnes et al. (2005) state that they have experimented with regressions distinguishing between Swedish and foreign customer, they do not report these results. Furthermore, they state that nationality does not make any significant difference in the results. However, they study only the SEK/EUR market and therefore they cannot find similar differences in different markets as I do. In other studies, in which more than one market is studied, to my best knowledge no one distinguishes between the nationalities of any customers and thus as I am able to distinguish between the country of origin of each single customer, my results are unique.

The R^2 statistics of the regressions are somewhat modest at the 1-day horizon, ranging from 7.5% to 17.3%. Evans and Lyons (2002a) report R^2 statistics of 46% for the Japanese yen/dollar market and 64% for the Deutsche mark/dollar market using daily data. However, their data sample spans only four months, compared to the range from nearly four to five years in my data set, depending on the foreign exchange market. Also, they model only the flows of market makers, which, in general, tend to match the foreign exchange rates the closest (see Appendix E).

A couple of reasons support the differences in the R^2 statistics between the different studied markets. First, in the USD/EUR market the market shares of my data set are minuscule and therefore the explanatory power of order flow remains small. Second, the DKK/EUR rate does not float completely freely as Denmark has agreed upon joining to the European Exchange Rate Mechanism (European Central Bank, 2005) and therefore the Danish krone is kept within a band of 2.25% against the central rate of DKK/EUR 7.46038. This limits the exchange rate fluctuations and thus the effect of order flow. In my data set Danish krone has stayed within a band of less than 0.5% against the central rate indicating that the Danish central bank has a strict control over the foreign exchange rate. On the other hand, Norwegian krone and Swedish krona are floating freely and also in those markets the market shares of my data set are considerable. As a result, the R^2 statistics are the highest in those markets.

Table 14 – Regression results at the 20-day horizon

	ΔCorp.	ΔState ow. comp.	ΔPublic inst.	ΔCentral bank	ΔMarket maker	ΔCredit inst.	ΔInsur. comp.	Trend	ΔDIF 10Y	ΔDIF 3M	R^2
DKK/EUR	-0.00031	-0.00100	-0.00005	-0.00047	-0.00015	0.00016	0.00005	-1.38E-07	0.00400	0.00282	88.17 %
	(-3.144)**	(-3.508)**	(-0.138)	(-5.273)**	(-2.819)**	(1.336)	(0.711)	(-0.515)	(6.08)**	(3.921)**	
NOK/EUR	-0.00323	-4.13071	-0.05453	-0.01705	0.01062	0.01955	-0.00704	3.30E-06	0.02220	0.00685	96.02 %
	(-1.805)	(-3.433)**	(-5.01)**	(-2.052)*	(9.422)**	(5.696)**	(-1.948)	(0.674)	(8.648)**	(2.505)*	
SEK/EUR	-0.00678	-0.00010	0.00290	0.01019	0.00449	0.01706	0.00793	5.65E-06	0.02409	0.02479	94.55 %
	(-5.323)**	(-0.008)	(0.847)	(3.422)**	(5.164)**	(5.82)**	(2.724)**	(1.434)	(8.486)**	(5.879)**	
USD/EUR	0.00632	-0.21721	0.03799	-0.00235	0.00743	0.03554	0.00865	-4.08E-07	0.02020	0.01091	93.99 %
	(4.199)**	(-3.513)**	(5.621)**	(-0.511)	(6.105)**	(7.324)**	(0.917)	(-0.046)	(7.848)**	(3.74)**	

Table 14 reports the results for the GMM regression $\Delta p_t = \beta_1 + \beta_2\Delta x_{t,i} + \beta_3\Delta(i_{10,t} - i^*_{10,t}) + \beta_4\Delta(i_{3,t} - i^*_{3,t}) + \beta_5 t + \beta_6 ECM(-n)$, where Δp_t is the change in log spot exchange rate from day *t-n* to day *t* and $\Delta x_{t,i}$ is the change in the order flow of customer type *i* from day *t-n* to day *t*. The regressor $\Delta(i_{10,t} - i^*_{10,t})$ is the change in the long-term interest rate differential between the euro area 10-year government bond and the foreign government bond from day *t-n* to day *t*, here ΔDIF 10Y. The regressor $\Delta(i_{3,t} - i^*_{3,t})$ is the change in the short-term interest rate differential between 3-month Euribor and the foreign equivalent from day *t-n* to day *t*, here ΔDIF 3M. Finally, regressor *t* is the linear trend and ECM(-n) is the error correction term, lagged *n* periods. *n* indicates the different time horizons over which the return is measured, here 20 days or 1 month. Order flow positions are measured in EUR 1 billion. Estimations are made using daily data and overlapping samples. The sample period spans from October 31, 2003 to February 28, 2008 for DKK/EUR and USD/EUR data, from May 23, 2003 to February 28, 2008 for NOK/EUR data and from May 24, 2004 to February 28, 2008 for SEK/EUR data. Coefficients (all insignificant) and error correction terms are not reported. A single asterisk (*) and two asterisks (**) denote significance at the 5% and 1% level, respectively.

When the regressions are run at the 20-day horizon (or 1 month), the explanatory power of the regressions becomes extremely good as the R^2 statistics immediately jump to the range of 88-96%. At the 60-day horizon (or 3 months), the R^2 statistics are all above 94%. This is quite impressive as Bjonnes et al. (2005) report R^2's of 48% and 50% for non-financial and financial customer in the SEK/EUR foreign exchange market at the 1-month horizon and around 70% at the 3-month horizon. The R^2 statistics of Fan and Lyons (2000) are 27% and 34% at the monthly horizon for euro vs. dollar and for yen vs. dollar, respectively. However, they do not use overlapping observations as Bjonnes et al. (2005) and I do.

This dramatic increase in the R^2 statistics may be explained by the fact that the different customer types are more diversified in my data set compared to the data set of Bjonnes et al. (2005). They study only the effect of financial and non-financial customer order flow whereas I have seven different customer types under study. The study of Fan and Lyons (2000) reports a similar increase in R^2 statistics. First they use the aggregate order flow to explain USD/EUR rate movements at monthly data and report R^2 statistic of 16%. After disaggregating their data set into three different customer types (unleveraged and leveraged financial customers and non-financial corporate customers), their reported R^2 statistic immediately nearly doubles to

27%. Similarly in their study for the yen vs. dollar market, the R^2 statistic increases from 15% to 34% after disaggregation. The above results hint that order flow is not simply undifferentiated demand but the source of order flow plays a key role, as the explanatory power of the regression increases so dramatically when the data is properly differentiated.

At the monthly horizon the majority of the regressors are significant, nearly all being significant at the 1% confidence level. Credit institutions and other market makers continue to be significant at 1% level with similar or slightly higher coefficients. This effect can also be seen in the regression at the 60-day horizon. Furthermore, the coefficient of market makers in the DKK/EUR market becomes significant at longer horizons but interestingly with an opposite sign compared to other markets. This could be explained by the fact that in the other markets, the customers from United Kingdom and United States dominate the market activity but in the DKK/EUR market the Nordic customers, especially Danish, play a major role. However, the coefficient is very close to zero both at the 1-month and 3-month horizon and the negative sign of the coefficient could just be a coincidence in my data set.

In addition, a larger portion of the interest rate differentials are significant with increased coefficients and t-statistics at the 20-day and 60-day horizons. Furthermore, all the significant coefficients of the interest rate differentials are always positive in these results meaning that an increase in the interest rate differential appreciated euro against the foreign currencies. As the coefficients of the long-term interest rate differentials are positive, the results may signal expectations of higher inflation in the foreign countries relative to the euro-zone countries.

State owned companies all have negative coefficients if they are statistically significant. In the DKK/EUR market the coefficient is -0.1% while in the USD/EUR and NOK/EUR markets the coefficients are extremely large, -22% and -413%, respectively, at the monthly horizon. In the NOK/EUR market the coefficient is -450% at the 3-month horizon. This is explained by the fact that order flow is measured per billion euros and the volume of state owned companies is minimalistic compared to one billion, except in the DKK/EUR market. Therefore the percentages are inflated considerably and the sign of the coefficient is more important than its size. Public institutions have negative coefficients in the NOK/EUR market and positive coefficient in the USD/EUR market. This is attributable to the fact that in the NOK/EUR market the public institutions are over 85% Norwegian (i.e. domestic) while in the USD/EUR market they are largely Finnish (i.e. foreign).

The only anomaly in the results of my data is the behaviour of the coefficients of insurance companies. At the 1-day and 1-month horizons the coefficients have positive signs in the SEK/EUR market but are insignificant in the other markets. However, at the 3-month horizon the coefficient is negative in the NOK/EUR market (it is also negative at the 1-day and 1-month horizons, although not significant) and remains positive in the SEK/EUR market (although slightly insignificant). This cannot be explained by the origin of the customers as over 50% of them are domestic (i.e. Norwegians in the NOK/EUR and Swedish in the SEK/EUR market) in both of these markets. Therefore, the effect of insurance companies' order flow is mixed across different markets.

Table 15 – Regression results at the 60-day horizon

	ΔCorp.	ΔState ow. comp.	ΔPublic inst.	ΔCentral bank	ΔMarket maker	ΔCredit inst.	ΔInsur. comp.	Trend	ΔDIF 10Y	ΔDIF 3M	R^2
DKK/EUR	-0.00031 (-3.501)**	-0.00141 (-4.63)**	-0.00020 (-0.521)	-0.00050 (-5.298)**	-0.00013 (-2.523)*	0.00007 (0.59)	-0.00003 (-0.469)	-2.17E-07 (-0.644)	0.00358 (6.346)**	0.00299 (3.08)**	94.66 %
NOK/EUR	-0.00221 (-1.323)	-4.50450 (-3.709)**	-0.03590 (-3.633)**	-0.01292 (-1.953)	0.00959 (9.214)**	0.01684 (4.889)**	-0.01168 (-2.873)**	5.13E-06 (0.804)	0.01852 (6.688)**	0.01040 (3.111)**	98.48 %
SEK/EUR	-0.00738 (-5.767)**	0.02022 (1.911)	0.00064 (0.202)	0.00233 (0.747)	0.00382 (4.234)**	0.01952 (7.373)**	0.00441 (1.89)	1.30E-05 (3.15)**	0.01987 (5.886)**	0.01831 (4.343)**	97.08 %
USD/EUR	0.00459 (3.32)**	-0.22186 (-6.443)**	0.03727 (5.247)**	-0.00878 (-2.095)*	0.00827 (8.203)**	0.03630 (7.827)**	-0.00144 (-0.169)	1.68E-05 (1.545)	0.01619 (5.884)**	0.00757 (1.758)	97.88 %

Table 15 reports the results for the GMM regression $\Delta p_t = \beta_1 + \beta_2\Delta x_{t,i} + \beta_3\Delta(i_{10,t} - i^*_{10,t}) + \beta_4\Delta(i_{3,t} - i^*_{3,t}) + \beta_5 t + \beta_6 ECM(-n)$, where Δp_t is the change in log spot exchange rate from day *t-n* to day *t* and $\Delta x_{t,i}$ is the change in the order flow of customer type *i* from day *t-n* to day *t*. The regressor $\Delta(i_{10,t} - i^*_{10,t})$ is the change in the long-term interest rate differential between the euro area 10-year government bond and the foreign government bond from day *t-n* to day *t*, here ΔDIF 10Y. The regressor $\Delta(i_{3,t} - i^*_{3,t})$ is the change in the short-term interest rate differential between 3-month Euribor and the foreign equivalent from day *t-n* to day *t*, here ΔDIF 3M. Finally, regressor *t* is the linear trend and ECM(-n) is the error correction term, lagged *n* periods. *n* indicates the different time horizons over which the return is measured, here 60 days or 3 months. Order flow positions are measured in EUR 1 billion. Estimations are made using daily data and overlapping samples. The sample period spans from October 31, 2003 to February 28, 2008 for DKK/EUR and USD/EUR data, from May 23, 2003 to February 28, 2008 for NOK/EUR data and from May 24, 2004 to February 28, 2008 for SEK/EUR data. Coefficients (all insignificant) and error correction terms are not reported. A single asterisk (*) and two asterisks (**) denote significance at the 5% and 1% level, respectively.

7.3.3. Price impact of the regression coefficients

The sizes of the significant order flow coefficients are considerable. For example, at the 1-day horizon, the coefficient of corporate customers' order flow in the NOK/EUR market indicates that if there are EUR 1 billion more purchases than sales by corporate customers, NOK/EUR exchange rate decreases by 0.681%, appreciating Norwegian krone. In other words, if measured at the closing rate of February 28, 2008, 7.859 NOK/EUR, the exchange rate would decrease over 535 price ticks or 0.054 krones. However, the 1-day standard deviation of the order flow positions of corporate customers is EUR 49 million, which would mean a price decrease of 0.0026 krones. At the same time, the standard deviation of the NOK/EUR rate at the 1-day horizon is 2.9% or over 0.22 krones.

In the USD/EUR market, 1 billion euro purchases in excess of sales conducted by corporate customers would increase the USD/EUR rate by 0.542% at the 1-day horizon or by 0.479% if measured by other market makers' order flow. At the closing rate of February 28, 2008 this would mean price increases of 82 and 73 price ticks, respectively. For credit institutions this impact is even higher: 1.97% or 300 price ticks per day. Evans and Lyons (2002a) find that USD 1 billion of net dollar purchases by other market makers increases the Deutsche mark price of a dollar by 0.54% or at the DM/USD rate of around 1.5 at that time, by 0.8 pfennig. Although they measure the DM/USD rate and not USD/EUR, the size of the impact is quite similar in my study.

When looking at the coefficients on a monthly basis, I find most of them larger as well as more significant. In the SEK/EUR market, the price impact of net EUR 1 billion purchases is 0.45% for market makers and 1.70% for credit institutions. At the closing foreign exchange rate on February 28, 2008 (9.3659 SEK/EUR) this means depreciation of the Swedish krona by 420 and 1,598 price ticks, or 0.042 and 0.160 kronas, respectively.

Bjonnes et al. (2005) report a coefficient 0.55% for financial customers at the 1-month horizon for net purchases of 10 billion Swedish kronas. As the cumulative order flow positions in my study are measured in billion euros, these figures need adjustment for comparison. At the closing price of February 28, 2008, this would mean 1,067 million euros and therefore a comparable coefficient for credit institutions' order flow of my study would be 1.82%, roughly three times the size reported by Bjonnes et al. (2005) for financial customers. At the 3-month horizon, comparable figure of my study would be 2.08% compared to 0.71% reported by Bjonnes et al. (2005). This means a depreciation of 0.1952 Swedish kronas per each 1 billion euro purchases in excess of euro sales by credit institutions in three months. The 3-month standard deviation of the order flow of the credit institutions is 173 million euros and thus net euro purchases of one standard deviation increases the SEK/EUR exchange rate by 0.36% or 338 price ticks. For comparison, the three month volatility of the

SEK/EUR rate is 2.11%. As the order flow of only credit institutions accounts for over 17% of the 3-month volatility of the SEK/EUR rate, the coefficients of my study are considerable.

After disaggregating their customer orders, Fan and Lyons (2000) report a coefficient of 1.5% for unleveraged financial customers at the 1-month horizon for net purchases of EUR 1 billion in the USD/EUR market. For leveraged financial customers and non-financial corporate customers their coefficients are 0.6% and -0.2% although they are not significant. In my data set the coefficient for corporate customers is 0.63%, 3.55% for credit institutions and 0.87% for insurance companies (although not significant) for net purchases of EUR 1 billion at the 1-month horizon. Therefore, the results of my data set are clearly consistent with the findings of Fan and Lyons (2000) with slightly higher coefficients. Even though the sign of corporate customers' coefficient is opposite, the results are similar as Fan and Lyons (2000) use data from Citibank and my data set is from a large Nordic bank with considerable activity from Norway and Denmark in this market.

The monthly volatility for the USD/EUR foreign exchange rate is 2.4% in my data set. At the February 28, 2008 price level the credit institutions' coefficient of 3.55% at the 1-month horizon means a foreign exchange rate increase of 539 price ticks for each billion euros bought more than sold in one months time. The 1-month standard deviation of the credit institutions' order flow is 200 million euros and thus the rate increase for a net order flow of one standard deviation would be 108 price ticks. For corporate customers' order flow the price increase is 34 price ticks for a net purchase equivalent of one standard deviation at the monthly horizon.

In the DKK/EUR market the coefficient are rather small at all time horizons. At the monthly horizon, corporate customers' order flow has an effect of -0.03%. For market makers and central banks the coefficients are -0.015% and -0.05%, respectively. The coefficients are similar at the 3-month horizon. The long and short-term interest rate differentials thus have the largest effect in the DKK/EUR market, 0.4% and 0.3%, respectively, both at the one and three month horizons. For comparison, the monthly volatility of the DKK/EUR rate is 0.1% in my data set.

The above regression results indicate that corporate customers provide liquidity on both short and long time horizons as their coefficients are negative (positive in the USD/EUR market as the customers are mainly Nordic). In addition, state owned companies, public institutions and central banks seem to be liquidity providers whereas credit institutions and insurance companies are liquidity takers. Furthermore, the cointegration results in the Section 7.1 as well as the above regression results suggest that the relation between order flows and foreign exchange rates have both short and long-term forms. The cointegration results indicate this long-term relation and as the t-statistics and coefficients tend to increase with longer time horizons in the regressions, this long-term relation is evident.

As the above results clearly show, customer order flows differ statistically significantly from zero in all the studied markets and time horizons. Therefore, Hypothesis 2 can be rejected. Furthermore, as different customer types have different impacts on the foreign exchange rates, Hypothesis 4 of similar market impacts can be rejected.

7.4. Causality

The following part discusses the effects of causality. Both the Anticipation hypothesis and the Feedback hypothesis are touched upon.

Hypothesis 5 states that lagged order flow affects price movements under the Anticipation hypothesis. This can be tested empirically by including a lagged order flow component, $\Delta x_{t-n,i}$, in the regression Eq. (13):

$$\Delta p_t = \beta_1 + \beta_2\Delta x_{t,i} + \beta_3\Delta x_{t-n,i} + \beta_4\Delta(i_{10,t} - i^*_{10,t}) + \beta_5\Delta(i_{3,t} - i^*_{3,t}) + \beta_6 t + \beta_7 ECM(-n) \quad (14)$$

The only change in Eq. (14) compared to the original Eq. (13) is the new lagged order flow component $\Delta x_{t-n,i}$. If the lagged order flow component is significant, it means that order flow affects the rate movements with a delay. If it is insignificant, I can state that the lagged order flow is already embedded in the price. The results of the regression Eq. (14) are presented in the Appendix C.

Adding the lagged order flow components into the regression improved the R^2 statistics of the regressions slightly at the 1-day horizon in all markets but at longer time horizons the R^2's stayed roughly the same as without the lagged order flow. Interestingly, some of the lagged components are significant: the lagged central bank order flow in the DKK/EUR market and the lagged order flows of state owned companies and public institutions in the NOK/EUR market at the 1-day horizon. Moreover, the lagged central bank coefficient has an opposite sign compared to the contemporaneous coefficient. At longer horizons, a larger share of the lagged order flow components is significant.

Furthermore, at the monthly horizon the lagged order flow of public institutions and credit institutions are significant in the DKK/EUR market while they are not contemporaneously significant. The same is true for central banks in the USD/EUR market. In the NOK/EUR market, a similar impact is seen for insurance companies at the 3-month horizon and for public institutions and state owned companies at the daily horizon. Adding the lagged components also reduced the significance of nearly all otherwise significant customer groups in all markets and time horizons.

In the DKK/EUR market, central banks' order flow affects both contemporaneously and with a 1-day delay. Also, the order flow of public institutions has a contemporaneous effect on the foreign exchange rate as well as an effect with a delay of both 20 and 60 days although it is insignificant at the 1-day horizon. In the NOK/EUR market, the lagged order flows of state owned companies and public institution are significant at the 5% confidence level. They are not, however, significant without the lag at the daily horizon.

As a conclusion, the anticipation Hypothesis 5 of the lagged order flow effects on the foreign exchange rate cannot be rejected completely in any of the studied markets, meaning that order flow affects foreign exchange rates at a delay for some customer types and with varying delays. The hypothesis is rejected, however, in the SEK/EUR market at the daily horizon and at the SEK/EUR and NOK/EUR markets at the 1-month horizon, where the lagged order flow components are insignificant and do not have a major effect on the significance of order flow components without the lag. Only the order flow of state owned companies became insignificant in the SEK/EUR market after the inclusion of the lagged components at the 1-day horizon. This means that the lagged order flows of all customer types in the SEK/EUR and in the NOK/EUR markets are already almost completely embedded in the foreign exchange rates.

The feedback trading issue of Hypothesis 6 can be tested using the following regression equation:

$$\Delta p_t = \beta_1 + \beta_2 \Delta x_{t,i} + \beta_3 \Delta p_{t-1} + \beta_4 \Delta(i_{10,t} - i^*_{10,t}) + \beta_5 \Delta(i_{3,t} - i^*_{3,t}) + \beta_6 t + \beta_7 ECM(-n), \quad (15)$$

where the only change compared to the original Eq. (13) is Δp_{t-1}, the lagged price movement component. This component catches the effect of feedback trading, should that exist in the data sample. If it is found significant, the effects of feedback trading were included in the coefficients of order flow components in Table 13 and therefore, their significance should be weakened. If the lagged price movement is insignificant, there is no evidence of feedback trading in my data set.

The following Table 16 presents the results of the regression with lagged price movement component.

Table 16 – Regression results including the lagged price movement component at the 1-day horizon

	ΔCorp.	ΔState ow. comp.	ΔPublic inst.	ΔCentral bank	ΔMarket maker	ΔCredit inst.	ΔInsur. comp.	Δp_{t-1}	ΔDIF 10Y	ΔDIF 3M	R^2
DKK/EUR	-0.00006	-0.00016	0.00072	-0.00043	-0.00007	0.00015	0.00009	-0.15233	0.00069	0.00086	10.26 %
	(-0.422)	(-0.463)	(1.21)	(-3.284)**	(-1.243)	(0.956)	(0.936)	(-0.694)	(1.386)	(0.981)	
NOK/EUR	-0.00709	-0.46103	-0.02986	-0.02421	0.01097	0.02138	-0.00463	-0.04090	0.00704	0.01466	17.40 %
	(-2.877)**	(-0.377)	(-1.922)	(-1.729)	(6.707)**	(4.355)**	(-0.842)	(-0.688)	(2.083)*	(2.787)**	
SEK/EUR	-0.00357	-0.04992	0.00119	0.00357	0.00599	0.01679	0.01051	0.04751	0.00786	0.02032	14.08 %
	(-1.938)	(-2.297)*	(0.264)	(0.843)	(4.464)**	(4.394)**	(3.366)**	(0.66)	(1.937)	(3.755)**	
USD/EUR	0.00517	-0.12404	0.00489	0.00605	0.00486	0.01932	0.01196	0.05521	0.01680	0.00768	7.59 %
	(2.525)*	(-3.772)**	(0.529)	(1.428)	(3.752)**	(4.27)**	(1.65)	(0.647)	(4.382)**	(1.641)	

Table 16 reports the results for the GMM regression $\Delta p_t = \beta_1 + \beta_2 \Delta x_{t,i} + \beta_3 \Delta p_{t-1} + \beta_4 \Delta(i_{10,t} - i^*_{10,t}) + \beta_5 \Delta(i_{3,t} - i^*_{3,t}) + \beta_6 t + \beta_7 ECM(-n)$, where Δp_t is the change in log spot exchange rate from day *t-n* to day *t* and $\Delta x_{t,i}$ is the change in the order flow of customer type *i* from day *t-n* to day *t*. Δp_{t-1} is the change in log spot exchange rate from day *t-n* to day *t*, lagged one period. The regressor $\Delta(i_{10,t} - i^*_{10,t})$ is the change in the long-term interest rate differential between the euro area 10-year government bond and the foreign government bond from day *t-n* to day *t*, here ΔDIF 10Y. The regressor $\Delta(i_{3,t} - i^*_{3,t})$ is the change in the short-term interest rate differential between 3-month Euribor and the foreign equivalent from day *t-n* to day *t*, here ΔDIF 3M. Finally, regressor *t* is the linear trend and ECM(-n) is the error correction term, lagged *n* periods. *n* indicates the different time horizons over which the return is measured, here 1 day. Order flow positions are measured in EUR 1 billion. Estimations are made using daily data and overlapping samples. The sample period spans from October 31, 2003 to February 28, 2008 for DKK/EUR and USD/EUR data, from May 23, 2003 to February 28, 2008 for NOK/EUR data and from May 24, 2004 to February 28, 2008 for SEK/EUR data. Coefficients (all insignificant), linear trends (all insignificant) and error correction terms are not reported. A single asterisk (*) and two asterisks (**) denote significance at the 5% and 1% level, respectively.

The above results regarding feedback trading in the data set are somewhat mixed. The lagged price movements are clearly insignificant in all studied markets and its' inclusion did not make any of the previously significant regressors as insignificant except for public institutions in the NOK/EUR market. In addition, the coefficient of order flow of the corporate customers in the USD/EUR market has become significant at the 5% confidence level instead of the previous 1% level. The other previously significant coefficients have remained at the same size and significance in all markets.

Although the coefficients of the two abovementioned customer types' order flow have become less significant, the Hypothesis 6 of feedback trading is rejected in all studied markets. The drop in the t-statistics for these customer types is not large (from 2.65 to 2.53 and from -2.02 to -1.92) and the remaining 15 other regressors did not lose any of their significance. Furthermore, the sizes of all coefficients remained roughly the same.

8. Conclusions

The objective of this thesis was to provide more answers to the question: What moves foreign exchange rates? More specifically, I intended to explain the short-term exchange rate movements in the Nordic region using order flow as the explanatory variable and study the impact of order flow from different customer types. Furthermore, I wanted to study the long-term relation between order flow and foreign exchange rates and examine the direction of causality. To answer these issues I used a unique data set of over 1.4 million actual FX-Spot and FX-Outright customer transactions from a large Nordic bank over a period spanning more than five years.

The results of this thesis suggest that the determination of the foreign exchange rates is clearly affected by order flow in the short term. This indicates that order flow truly conveys information. These findings are in line with the previous academic research in this area. Furthermore, in the cointegration analysis, I find that there is a long-term relation between order flow and foreign exchange rates. Finally, the findings show no evidence of feedback trading, which suggests that the direction of causality runs from order flow to foreign exchange rates and not from foreign exchange rates to order flow.

The estimates of this thesis can explain 8-17% of the daily changes in the foreign exchange rates, depending on the market under study. Moreover, at longer horizons (monthly and quarterly) the explanatory power of the estimates increases to over 80% of the variation in the exchange rates. The results show that different customer types have different short-term impacts on the exchange rates: corporate customers, state owned companies, public institutions and central banks cause a negative correlation between order flow and exchange rates whereas other market makers, credit institutions and insurance companies induce a positive correlation. Furthermore, the sizes of the order flow coefficients for each customer type are different, indicating that different customer types have different short-term impacts on the exchange rates. Finally, the findings show that some of the effects of order flow are evident at a delay, depending on the market and customer type.

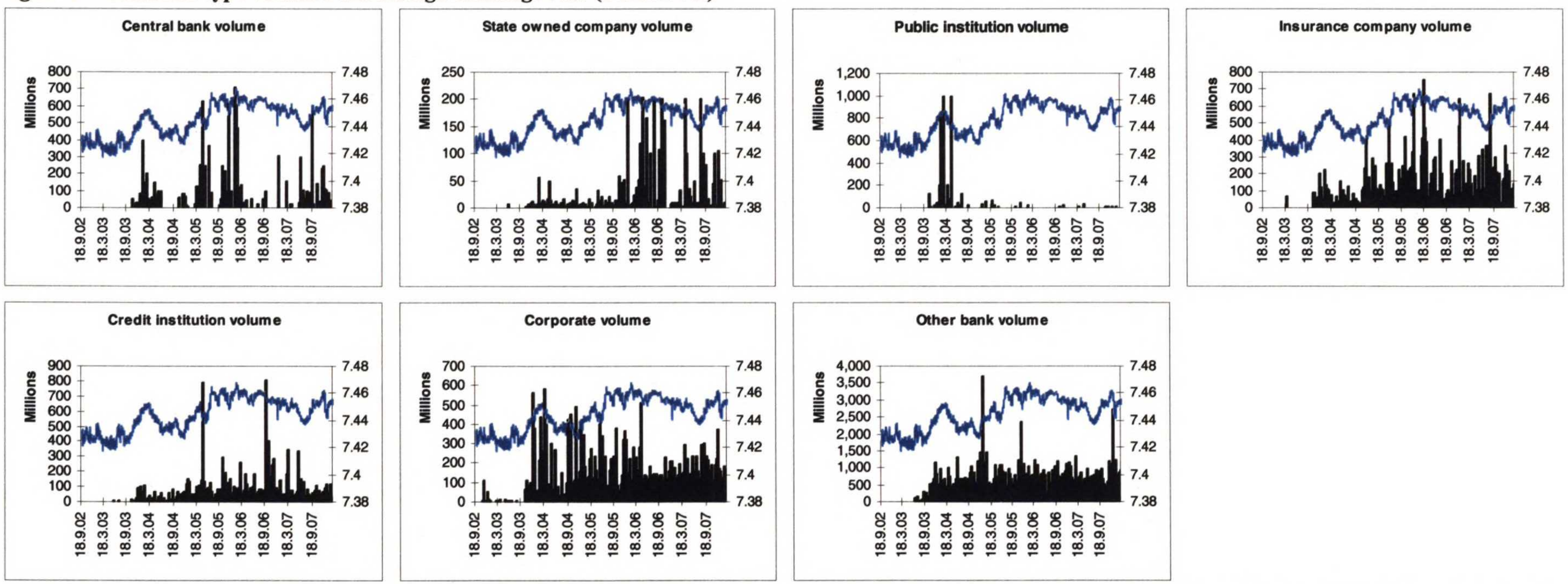
As the role of order flow in transmitting information to foreign exchange rates has been verified, one may ask for the driving force behind order flow and what causes order flow. This would be an important area for future research. As the previous academic literature on market microstructure and this thesis have indicated, order flow is a proximate cause for exchange rate movements, transmitting information about fundamentals into exchange rates. Because different customer types produce order flow with different impacts on exchange rates, understanding the information driving order flow of these customer types would be an ideal focus for future research. Moreover, research about different trading strategies based on the informational value of order flow could expand the exchange rate determination puzzle into concrete business-oriented solutions which could be used by the market makers.

Appendices

A. Volumes per customer type

The following Fig. 3 presents graphs of the DKK/EUR volume (in million euros) for different customer types (left axis) and the DKK/EUR exchange rate (right axis). Note how thin the public institution volume is except for the first half of 2004.

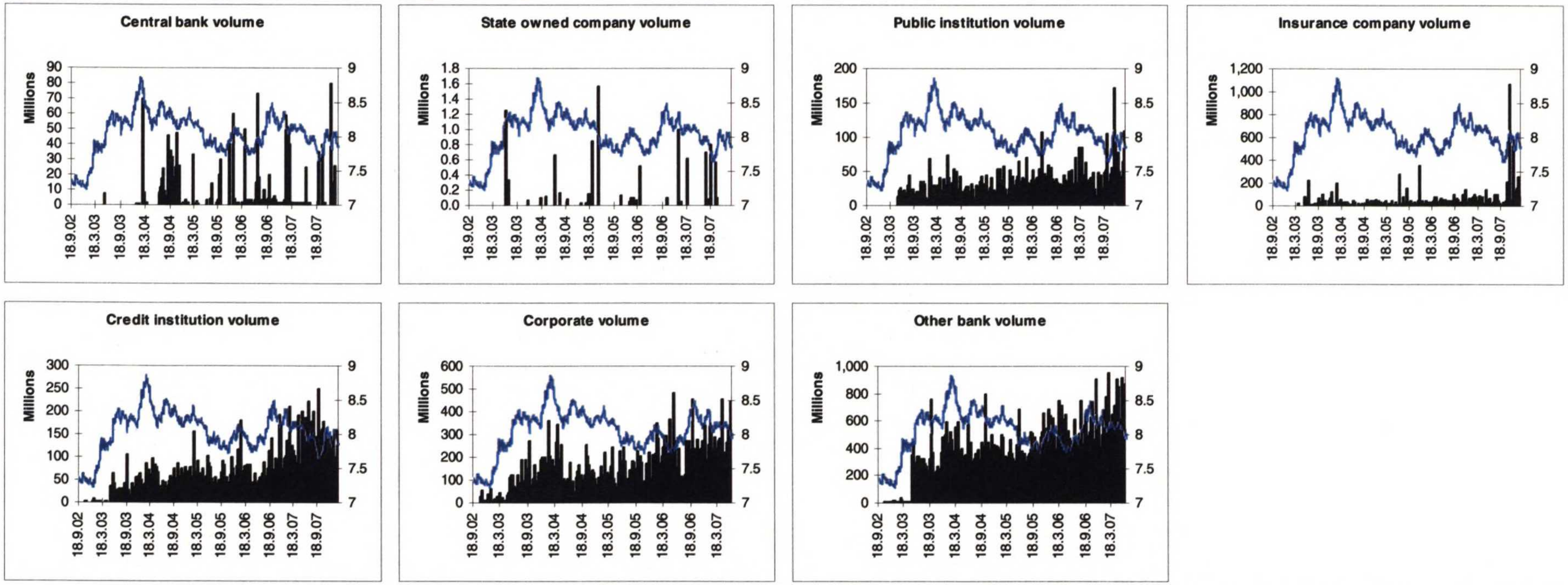
Figure 3 – Customer type volumes and foreign exchange rate (DKK/EUR)



The above figure presents seven graphs of the DKK/EUR volume (in million euros) for different customer types and the DKK/EUR exchange rate. The data period spans in each graph from September 18, 2002 to February 28, 2008.

The following figure presents graphs of the NOK/EUR volume (in million euros) for different customer types (left axis) and the NOK/EUR exchange rate (right axis). Note how the volume of state owned companies is very weak.

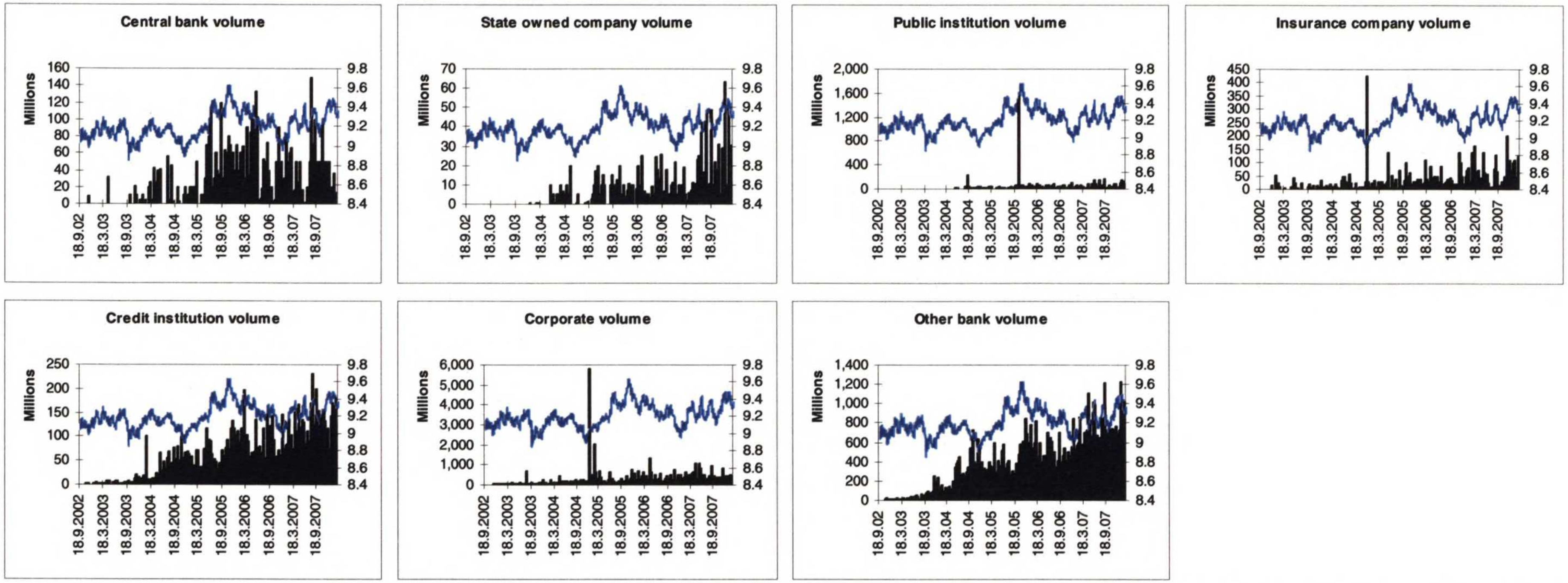
Figure 4 – Customer type volumes and foreign exchange rate (NOK/EUR)



The above figure presents seven graphs of the NOK/EUR volume (in million euros) for different customer types and the NOK/EUR exchange rate. The data period spans in each graph from September 18, 2002 to February 28, 2008.

The following figure presents graphs of the SEK/EUR volume (in million euros) for different customer types (left axis) and the SEK/EUR exchange rate (right axis). Note the spike of over 1.5 billion euros in public institution volume in October 2005 versus how thin the volume is during other periods. Also, note the enormous volume of nearly 6 billion euros in corporate volume in just before year end 2004.

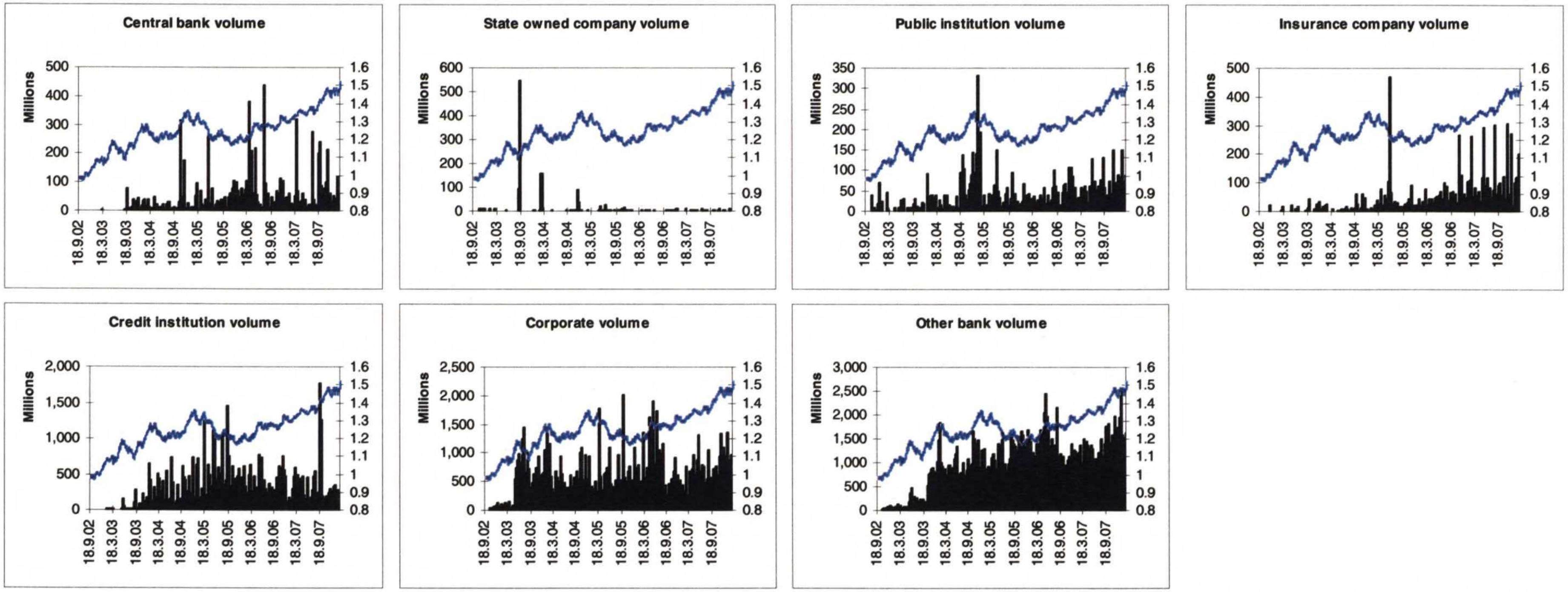
Figure 5 – Customer type volumes and foreign exchange rate (SEK/EUR)



This figure presents seven graphs of the SEK/EUR volume (in million euros) for different customer types and the SEK/EUR exchange rate. The data period spans in each graph from September 18, 2002 to February 28, 2008.

The following figure presents graphs of the USD/EUR volume (in million euros) for different customer types (left axis) and the USD/EUR exchange rate (right axis). Note how the volume of state owned companies is very thin except for early September 2003.

Figure 6 – Customer type volumes and foreign exchange rate (USD/EUR)



The above figure presents seven graphs of the USD/EUR volume (in million euros) for different customer types and the USD/EUR exchange rate. The data period spans in each graph from September 18, 2002 to February 28, 2008.

B. Country split of different customer types

The following Table 17 presents the top three shares of turnover split by the origin of the counterparty for different customer types.

Table 17 – Country split of different customer types

Panel A DKK/EUR

Central bank		Corporate		Credit inst.		Market maker		Insurance company		Public inst.		State own. comp.	
Country	**Share**	**Country**	**Share**	**Country**	**Share**	**Country**	**Share**	**Country**	**Share**	**Country**	**Share**	**Country**	**Share**
Denmark	79.1 %	Denmark	83.2 %	Denmark	47.2 %	Sweden	29.0 %	Denmark	99.9 %	Denmark	90.6 %	Denmark	51.2 %
Portugal	10.0 %	Finland	3.5 %	United States	23.4 %	Denmark	23.3 %	Finland	0.1 %	Finland	6.8 %	Finland	48.7 %
Norway	6.6 %	Sweden	3.4 %	United Kingdom	16.8 %	United Kingdom	8.0 %	Norway	0.0 %	Norway	1.6 %	Sweden	0.0 %

Panel B - NOK/EUR

Central bank		Corporate		Credit inst.		Market maker		Insurance company		Public inst.		State own. comp.	
Country	**Share**	**Country**	**Share**	**Country**	**Share**	**Country**	**Share**	**Country**	**Share**	**Country**	**Share**	**Country**	**Share**
Norway	49.9 %	Norway	68.8 %	United States	24.6 %	Sweden	15.4 %	Norway	53.6 %	Norway	86.2 %	Finland	96.3 %
Portugal	32.9 %	Finland	14.6 %	Denmark	23.4 %	United Kingdom	15.1 %	Finland	7.8 %	Finland	11.2 %	United Stated	3.0 %
United Kingdom	9.8 %	Sweden	5.0 %	United Kingdom	20.0 %	Norway	15.0 %	Sweden	3.8 %	Sweden	2.6 %	Denmark	0.8 %

Panel C - SEK/EUR

Central bank		Corporate		Credit inst.		Market maker		Insurance company		Public inst.		State own. comp.	
Country	**Share**	**Country**	**Share**	**Country**	**Share**	**Country**	**Share**	**Country**	**Share**	**Country**	**Share**	**Country**	**Share**
Norway	83.7 %	Sweden	54.7 %	United Kingdom	27.3 %	United Kingdom	21.6 %	Sweden	58.8 %	Finland	61.2 %	Finland	82.7 %
Portugal	8.1 %	Finland	31.3 %	United States	23.4 %	Sweden	18.8 %	Finland	22.4 %	Sweden	34.2 %	Sweden	17.1 %
Sweden	2.7 %	Norway	4.6 %	Denmark	22.3 %	United States	15.9 %	Denmark	7.6 %	Norway	4.6 %	Denmark	0.1 %

Panel D - USD/EUR

Central bank		Corporate		Credit inst.		Market maker		Insurance company		Public inst.		State own. comp.	
Country	**Share**	**Country**	**Share**	**Country**	**Share**	**Country**	**Share**	**Country**	**Share**	**Country**	**Share**	**Country**	**Share**
Norway	45.3 %	Norway	62.4 %	Norway	24.1 %	United States	22.4 %	Finland	37.8 %	Finland	87.5 %	Finland	85.9 %
Denmark	22.5 %	Finland	21.5 %	Denmark	23.4 %	United Kingdom	12.4 %	Denmark	28.5 %	Sweden	7.1 %	Denmark	13.0 %
France	4.4 %	Sweden	5.1 %	United States	22.3 %	Belgium	9.7 %	Sweden	6.6 %	Norway	3.0 %	Latvia	1.1 %

The above table presents top three shares of turnover split by the origin of the counterparty for different customer types. Panel A presents DKK/EUR market, panel B NOK/EUR, panel C SEK/EUR and panel D presents the USD/EUR market.

C. Regression results with lagged order flow

The following tables present the regression results with lagged order flow components at the 1-day, 1-month and 3-month horizons.

Table 18 – Regression results at the 1-day horizon with lagged order flow components

	ΔCorp.	ΔState ow. comp.	ΔPublic inst.	ΔCentral bank	ΔMarket maker	ΔCredit inst.	ΔInsur. comp.	ΔCorp. (-1)	ΔState ow. comp. (-1)	ΔPublic inst. (-1)	ΔCentral bank (-1)	ΔMarket maker (-1)	ΔCredit inst. (-1)	ΔInsur. comp. (-1)	Trend	ΔDIF 10Y	ΔDIF 3M	R^2
DKK/EUR	-0.00012	-0.00034	0.00086	-0.00056	-0.00008	0.00010	0.00008	-0.00009	0.00024	-0.00070	0.00033	-0.00004	-0.00001	-0.00012	0.00000	4.76E-04	-0.00049	10.36 %
	(-1.082)	(-1.066)	(1.414)	(-3.457)**	(-1.062)	(0.557)	(0.847)	(-0.694)	(0.975)	(-1.408)	(3.024)**	(-0.687)	(-0.048)	(-1.236)	(-0.466)	(1.123)	(-0.43)	
NOK/EUR	-0.00473	-1.51536	-0.02494	-0.02903	0.01134	0.02241	0.00080	0.00283	2.74769	-0.02289	-0.00200	-0.00163	0.00009	-0.00381	0.00000	7.70E-03	0.01712	18.10 %
	(-1.903)	(-1.121)	(-1.676)	(-1.979)*	(6.937)**	(4.574)**	(0.152)	(1.247)	(2.252)*	(-2.355)*	(-0.169)	(-1.175)	(0.022)	(-0.805)	(0.206)	(2.212)*	(3.318)**	
SEK/EUR	-0.00340	-0.02818	-0.00303	0.00538	0.00682	0.01723	0.01017	-0.00048	0.00669	0.00681	-0.00233	-0.00142	0.00407	0.00255	0.00000	6.09E-03	0.02030	14.37 %
	(-1.706)	(-1.687)	(-0.631)	(1.184)	(4.394)**	(4.3)**	(3.05)**	(-0.309)	(0.401)	(1.068)	(-0.623)	(-1.394)	(1.113)	(0.728)	(0.458)	(1.521)	(3.541)**	
USD/EUR	0.00523	-0.12059	0.00595	0.00427	0.00444	0.02113	0.01116	-0.00117	0.01754	0.01186	-0.00644	-0.00010	-0.00069	0.00323	0.00000	1.90E-02	0.00805	7.66 %
	(2.578)**	(-3.734)**	(0.647)	(1.024)	(3.328)**	(4.685)**	(1.509)	(-0.587)	(0.718)	(1.266)	(-1.778)	(-0.074)	(-0.206)	(0.6)	(-0.021)	(4.968)**	(1.705)	

Table 18 reports the results for the GMM regression $\Delta p_t = \beta_1 + \beta_2\Delta x_{t,i} + \beta_3\Delta x_{t-n,i} + \beta_4\Delta(i_{10,t} - i^*_{10,t}) + \beta_5\Delta(i_{3,t} - i^*_{3,t}) + \beta_6 t + \beta_7 ECM(-n)$, where Δp_t is the change in log spot exchange rate from day *t-n* to day *t* and $\Delta x_{t,i}$ is the change in the order flow of customer type *i* from day *t-n* to day *t*. $\Delta x_{t-1,i}$ is the change in the order flow of customer type *i* from day *t-n* to day *t*, lagged *n* periods. The regressor $\Delta(i_{10,t} - i^*_{10,t})$ is the change in the long-term interest rate differential between the euro area 10-year government bond and the foreign government bond from day *t-n* to day *t*, here ΔDIF 10Y. The regressor $\Delta(i_{3,t} - i^*_{3,t})$ is the change in the short-term interest rate differential between 3-month Euribor and the foreign equivalent from day *t-n* to day *t*, here ΔDIF 3M. Finally, regressor *t* is the linear trend and ECM(-n) is the error correction term, lagged *n* periods. *n* indicates the different time horizons over which the return is measured, here 1 day. Order flow positions are measured in EUR 1 billion. Estimations are made using daily data and overlapping samples. The sample period spans from October 31, 2003 to February 28, 2008 for DKK/EUR and USD/EUR data, from May 23, 2003 to February 28, 2008 for NOK/EUR data and from May 24, 2004 to February 28, 2008 for SEK/EUR data. Coefficients (all insignificant) and error correction terms are not reported.

Table 19 – Regression results at the 20-day horizon with lagged order flow components

	ΔCorp.	ΔState ow. comp.	ΔPublic inst.	ΔCentral bank	ΔMarket maker	ΔCredit inst.	ΔInsur. comp.	ΔCorp. (-20)	ΔState ow. comp. (-20)	ΔPublic inst. (-20)	ΔCentral bank (-20)	ΔMarket maker (-20)	ΔCredit inst. (-20)	ΔInsur. comp. (-20)	Trend	ΔDIF 10Y	ΔDIF 3M	R^2
DKK/EUR	-0.00025	-0.00072	0.00045	-0.00042	-0.00016	0.00002	0.00007	0.00013	0.00074	0.00091	0.00011	0.00001	-0.00022	0.00007	0.00000	4.58E-03	0.00233	88.24 %
	(-2.387)*	(-2.223)*	(1.249)	(-3.919)**	(-2.406)*	(0.184)	(0.799)	(1.163)	(3.322)**	(3.487)**	(1.225)	(0.24)	(-2.043)*	(0.872)	(0.459)	(6.585)**	(3.634)**	
NOK/EUR	-0.00285	-3.93103	-0.06189	-0.02035	0.00979	0.02146	-0.00613	0.00017	1.26445	-0.01470	-0.01196	-0.00070	0.00154	0.00055	0.00000	2.28E-02	0.00563	95.91 %
	(-1.422)	(-2.87)**	(-4.511)**	(-2.267)*	(7.884)**	(5.297)**	(-1.66)	(0.085)	(1.298)	(-1.29)	(-1.711)	(-0.643)	(0.351)	(0.146)	(-0.042)	(8.793)**	(2.111)*	
SEK/EUR	-0.00567	-0.00673	0.00399	0.01024	0.00530	0.01593	0.00873	0.00187	-0.01622	-0.00019	-0.00365	0.00114	-0.00252	0.00248	0.00001	2.28E-02	0.02646	94.61 %
	(-3.815)**	(-0.497)	(1.081)	(2.943)**	(5.366)**	(5.291)**	(3.052)**	(1.522)	(-1.106)	(-0.043)	(-1.042)	(1.254)	(-0.861)	(0.913)	(1.889)	(8.058)**	(6.367)**	
USD/EUR	0.00685	-0.16493	0.02433	-0.00017	0.00667	0.03199	0.00703	0.00216	0.08143	-0.02858	0.00953	-0.00042	-0.01151	0.00059	0.00000	1.96E-02	0.00895	93.75 %
	(3.989)**	(-4.132)**	(3.064)**	(-0.044)	(5.423)**	(6.26)**	(0.738)	(1.255)	(1.536)	(-3.631)**	(2.413)*	(-0.382)	(-2.538)*	(0.067)	(-0.004)	(7.507)**	(2.89)**	

Table 19 reports the results for the GMM regression $\Delta p_t = \beta_1 + \beta_2\Delta x_{t,i} + \beta_3\Delta x_{t-n,i} + \beta_4\Delta(i_{10,t} - i^*_{10,t}) + \beta_5\Delta(i_{3,t} - i^*_{3,t}) + \beta_6 t + \beta_7 ECM(-n)$, where Δp_t is the change in log spot exchange rate from day *t-n* to day *t* and $\Delta x_{t,i}$ is the change in the order flow of customer type *i* from day *t-n* to day *t*. $\Delta x_{t-1,i}$ is the change in the order flow of customer type *i* from day *t-n* to day *t*, lagged *n* periods. The regressor $\Delta(i_{10,t} - i^*_{10,t})$ is the change in the long-term interest rate differential between the euro area 10-year government bond and the foreign government bond from day *t-n* to day *t*, here ΔDIF 10Y. The regressor $\Delta(i_{3,t} - i^*_{3,t})$ is the change in the short-term interest rate differential between 3-month Euribor and the foreign equivalent from day *t-n* to day *t*, here ΔDIF 3M. Finally, regressor *t* is the linear trend and ECM(-n) is the error correction term, lagged *n* periods. *n* indicates the different time horizons over which the return is measured, here 20 days or 1 month. Order flow positions are measured in EUR 1 billion. Estimations are made using daily data and overlapping samples. The sample period spans from October 31, 2003 to February 28, 2008 for DKK/EUR and USD/EUR data, from May 23, 2003 to February 28, 2008 for NOK/EUR data and from May 24, 2004 to February 28, 2008 for SEK/EUR data. Coefficients (all insignificant) and error correction terms are not reported.

Table 20 – Regression results at the 60-day horizon with lagged order flow components

	ΔCorp.	ΔState ow. comp.	ΔPublic inst.	ΔCentral bank	ΔMarket maker	ΔCredit inst.	ΔInsur. comp.	ΔCorp. (-60)	ΔState ow. comp. (-60)	ΔPublic inst. (-60)	ΔCentral bank (-60)	ΔMarket maker (-60)	ΔCredit inst. (-60)	ΔInsur. comp. (-60)	Trend	ΔDIF 10Y	ΔDIF 3M	R^2
DKK/EUR	-0.00030 (-2.691)**	-0.00129 (-4.139)**	-0.00130 (-2.562)*	-0.00048 (-4.685)**	-0.00015 (-2.508)*	0.00003 (0.276)	-0.00008 (-1.308)	0.00013 (1.258)	0.00042 (1.62)	-0.00137 (-3.384)**	0.00016 (1.588)	0.00002 (0.434)	0.00002 (0.202)	-0.00004 (-0.751)	0.00000 (-1.099)	3.32E-03 (6.555)**	0.00337 (3.525)**	94.51 %
NOK/EUR	-0.00501 (-2.824)**	-2.78922 (-2.271)*	-0.03083 (-2.798)**	-0.01617 (-2.619)**	0.00785 (6.632)**	0.01313 (3.627)**	-0.00549 (-1.535)	-0.00449 (-2.257)*	1.73616 (1.986)*	0.01766 (1.582)	0.00240 (0.4)	-0.00153 (-1.355)	-0.00631 (-1.843)	0.01037 (2.479)*	0.00001 (1.543)	1.46E-02 (5.54)**	0.01250 (3.426)**	98.57 %
SEK/EUR	-0.00451 (-3.082)**	0.02215 (2.127)*	0.00202 (0.633)	0.00556 (1.554)	0.00608 (5.896)**	0.02171 (7.779)**	0.00529 (2.011)*	0.00314 (2.461)*	-0.01628 (-1.295)	0.00031 (0.079)	0.00440 (1.259)	0.00166 (1.924)	0.00710 (2.731)**	0.00175 (0.678)	0.00002 (2.838)**	1.91E-02 (5.598)**	0.01586 (3.721)**	97.04 %
USD/EUR	0.00362 (2.229)*	-0.16620 (-4.563)**	0.02650 (3.578)**	-0.00465 (-1.117)	0.00642 (5.06)**	0.04300 (6.19)**	-0.02288 (-1.67)	-0.00091 (-0.615)	0.07512 (1.43)	-0.02736 (-3.338)**	0.00470 (1.179)	-0.00271 (-2.4)*	-0.00628 (-1.63)	-0.00863 (-0.992)	0.00001 (0.935)	1.59E-02 (5.971)**	0.00911 (2.116)*	97.90 %

Table 20 reports the results for the GMM regression $\Delta p_t = \beta_1 + \beta_2\Delta x_{t,i} + \beta_3\Delta x_{t-n,i} + \beta_4\Delta(i_{10,t} - i^*_{10,t}) + \beta_5\Delta(i_{3,t} - i^*_{3,t}) + \beta_6 t + \beta_7 ECM(-n)$, where Δp_t is the change in log spot exchange rate from day *t-n* to day *t* and $\Delta x_{t,i}$ is the change in the order flow of customer type *i* from day *t-n* to day *t*. $\Delta x_{t-1,i}$ is the change in the order flow of customer type *i* from day *t-n* to day *t*, lagged *n* periods. The regressor $\Delta(i_{10,t} - i^*_{10,t})$ is the change in the long-term interest rate differential between the euro area 10-year government bond and the foreign government bond from day *t-n* to day *t*, here ΔDIF 10Y. The regressor $\Delta(i_{3,t} - i^*_{3,t})$ is the change in the short-term interest rate differential between 3-month Euribor and the foreign equivalent from day *t-n* to day *t*, here ΔDIF 3M. Finally, regressor *t* is the linear trend and ECM(-n) is the error correction term, lagged *n* periods. *n* indicates the different time horizons over which the return is measured, here 60 days or 3 months. Order flow positions are measured in EUR 1 billion. Estimations are made using daily data and overlapping samples. The sample period spans from October 31, 2003 to February 28, 2008 for DKK/EUR and USD/EUR data, from May 23, 2003 to February 28, 2008 for NOK/EUR data and from May 24, 2004 to February 28, 2008 for SEK/EUR data. Coefficients (all insignificant) and error correction terms are not reported.

D. Pairwise correlation matrices

The following tables present the pairwise correlation matrices of different customer types in all the studied markets.

Table 21 – DKK/EUR pairwise correlation matrix

		Central bank	Corporate	Credit inst.	Insurance company	Market maker	Public inst.	State own. comp.	Diff 10y	Diff 3m
Central bank	(1-day)	1.00								
	(20-day)	1.00								
	(60-day)	1.00								
Corporate	(1-day)	-0.03	1.00							
	(20-day)	0.18	1.00							
	(60-day)	0.34	1.00							
Credit institution	(1-day)	-0.19	-0.02	1.00						
	(20-day)	-0.16	-0.08	1.00						
	(60-day)	-0.19	-0.12	1.00						
Insurance company	(1-day)	-0.01	0.03	-0.02	1.00					
	(20-day)	0.01	0.27	-0.08	1.00					
	(60-day)	0.40	0.19	-0.17	1.00					
Market maker	(1-day)	-0.16	-0.24	-0.13	-0.40	1.00				
	(20-day)	-0.35	-0.55	-0.09	-0.60	1.00				
	(60-day)	-0.48	-0.56	-0.12	-0.62	1.00				
Public institution	(1-day)	-0.03	-0.01	0.00	0.00	-0.07	1.00			
	(20-day)	-0.19	-0.06	0.04	0.00	-0.05	1.00			
	(60-day)	-0.28	0.18	0.09	-0.03	-0.09	1.00			
State owned company	(1-day)	0.00	0.03	-0.07	-0.01	-0.09	0.00	1.00		
	(20-day)	0.14	0.21	-0.11	0.04	-0.26	0.01	1.00		
	(60-day)	0.14	0.44	-0.15	0.16	-0.47	0.08	1.00		
Diff 10y	(1-day)	-0.01	0.02	0.06	0.01	-0.04	0.01	-0.04	1.00	
	(20-day)	0.08	0.03	0.04	0.03	0.04	-0.07	0.01	1.00	
	(60-day)	0.06	0.05	-0.02	0.14	-0.08	-0.05	0.18	1.00	
Diff 3m	(1-day)	0.06	-0.04	0.02	-0.01	-0.08	0.03	-0.08	0.03	1.00
	(20-day)	0.27	0.08	0.01	0.06	0.00	-0.03	-0.15	0.11	1.00
	(60-day)	0.54	0.16	0.04	0.34	-0.26	-0.08	-0.02	0.11	1.00

The above table presents the pairwise correlation matrix for DKK/EUR. Each subsection is divided into 3 panels, illustrating the 1-day, 20-day and 60-day correlation matrixes of appropriate customer type or interest rate differential. The data period spans from October 31, 2003 to February 28, 2008. All positions are measured in EUR 10 million.

Table 22 – NOK/EUR pairwise correlation matrix

		Central bank	Corporate	Credit inst.	Insurance company	Market maker	Public inst.	State own. comp.	Diff 10y	Diff 3m
Central bank	(1-day)	1.00								
	(20-day)	1.00								
	(60-day)	1.00								
Corporate	(1-day)	0.02	1.00							
	(20-day)	0.14	1.00							
	(60-day)	0.11	1.00							
Credit institution	(1-day)	-0.09	-0.36	1.00						
	(20-day)	-0.03	-0.63	1.00						
	(60-day)	-0.02	-0.67	1.00						
Insurance company	(1-day)	-0.04	-0.14	-0.07	1.00					
	(20-day)	-0.22	-0.12	-0.11	1.00					
	(60-day)	-0.25	-0.30	0.04	1.00					
Market maker	(1-day)	-0.12	-0.51	0.34	-0.11	1.00				
	(20-day)	-0.25	-0.75	0.50	-0.04	1.00				
	(60-day)	-0.34	-0.83	0.40	0.28	1.00				
Public institution	(1-day)	0.03	0.02	-0.04	-0.01	-0.13	1.00			
	(20-day)	0.20	-0.02	0.03	-0.18	0.07	1.00			
	(60-day)	0.27	0.02	0.01	-0.09	-0.14	1.00			
State owned company	(1-day)	0.00	0.03	-0.01	0.02	-0.04	0.01	1.00		
	(20-day)	-0.04	0.16	-0.17	0.12	-0.26	-0.06	1.00		
	(60-day)	-0.09	0.20	-0.05	-0.06	-0.28	-0.07	1.00		
Diff 10y	(1-day)	-0.02	0.00	0.03	-0.10	0.04	0.02	0.02	1.00	
	(20-day)	-0.08	-0.10	0.26	-0.14	0.14	0.04	0.00	1.00	
	(60-day)	-0.14	-0.13	0.34	0.00	0.22	0.08	-0.13	1.00	
Diff 3m	(1-day)	-0.01	-0.06	0.08	-0.09	0.06	-0.04	0.00	0.13	1.00
	(20-day)	0.00	-0.24	0.34	-0.33	0.21	0.22	-0.28	0.31	1.00
	(60-day)	0.00	-0.33	0.44	-0.28	0.25	0.35	-0.15	0.40	1.00

The above table presents the pairwise correlation matrix for NOK/EUR. Each subsection is divided into 3 panels, illustrating the 1-day, 20-day and 60-day correlation matrixes of appropriate customer type or interest rate differential. The data period spans from May 23, 2003 to February 28, 2008. All positions are measured in EUR 10 million.

Table 23 – SEK/EUR pairwise correlation matrix

		Central bank	Corporate	Credit inst.	Insurance company	Market maker	Public inst.	State own. comp.	Diff 10y	Diff 3m
Central bank	(1-day)	1.00								
	(20-day)	1.00								
	(60-day)	1.00								
Corporate	(1-day)	-0.06	1.00							
	(20-day)	0.02	1.00							
	(60-day)	0.02	1.00							
Credit institution	(1-day)	-0.07	-0.23	1.00						
	(20-day)	-0.19	-0.46	1.00						
	(60-day)	-0.37	-0.51	1.00						
Insurance company	(1-day)	-0.02	0.03	-0.08	1.00					
	(20-day)	0.04	0.22	-0.32	1.00					
	(60-day)	0.03	0.22	-0.33	1.00					
Market maker	(1-day)	-0.14	-0.46	0.29	-0.22	1.00				
	(20-day)	-0.17	-0.57	0.53	-0.25	1.00				
	(60-day)	-0.26	-0.54	0.50	-0.03	1.00				
Public institution	(1-day)	0.01	0.07	-0.14	-0.02	-0.20	1.00			
	(20-day)	0.22	-0.04	-0.15	0.04	-0.25	1.00			
	(60-day)	0.43	-0.38	0.22	-0.29	0.00	1.00			
State owned company	(1-day)	-0.01	0.08	-0.05	-0.05	-0.08	-0.01	1.00		
	(20-day)	0.03	-0.04	0.08	-0.13	0.13	-0.16	1.00		
	(60-day)	0.05	-0.11	-0.07	-0.25	0.09	-0.04	1.00		
Diff 10y	(1-day)	0.00	-0.03	0.03	-0.03	0.05	0.02	-0.02	1.00	
	(20-day)	-0.08	-0.06	0.08	-0.04	0.01	-0.06	-0.21	1.00	
	(60-day)	-0.23	0.00	0.19	0.11	0.11	-0.13	-0.50	1.00	
Diff 3m	(1-day)	-0.08	0.03	0.09	-0.03	0.07	-0.09	-0.03	0.14	1.00
	(20-day)	0.03	-0.05	0.17	0.04	0.19	-0.23	0.00	0.42	1.00
	(60-day)	-0.19	0.07	0.06	0.25	0.19	-0.37	-0.14	0.44	1.00

The above table presents the pairwise correlation matrix for SEK/EUR. Each section is divided into 3 panels, illustrating the 1-day, 20-day and 60-day correlation matrixes of appropriate customer type or interest rate differential. The data period spans from May 24, 2004 to February 28, 2008. All positions are measured in EUR 10 million.

Table 24 – USD/EUR pairwise correlation matrix

		Central bank	Corporate	Credit inst.	Insurance company	Market maker	Public inst.	State own. comp.	Diff 10y	Diff 3m
Central bank	(1-day)	1.00								
	(20-day)	1.00								
	(60-day)	1.00								
Corporate	(1-day)	0.00	1.00							
	(20-day)	0.04	1.00							
	(60-day)	-0.11	1.00							
Credit institution	(1-day)	-0.12	-0.17	1.00						
	(20-day)	-0.14	-0.02	1.00						
	(60-day)	-0.27	0.10	1.00						
Insurance company	(1-day)	0.02	0.00	-0.44	1.00					
	(20-day)	0.22	0.02	-0.46	1.00					
	(60-day)	0.23	0.16	-0.37	1.00					
Market maker	(1-day)	-0.21	-0.41	0.25	-0.07	1.00				
	(20-day)	-0.33	-0.21	0.35	-0.23	1.00				
	(60-day)	-0.28	-0.12	0.31	-0.33	1.00				
Public institution	(1-day)	-0.07	0.08	-0.07	-0.03	-0.12	1.00			
	(20-day)	-0.13	0.05	-0.26	0.09	-0.09	1.00			
	(60-day)	-0.06	0.28	-0.33	0.10	-0.19	1.00			
State owned company	(1-day)	-0.01	0.00	-0.01	0.01	-0.01	-0.03	1.00		
	(20-day)	0.17	0.03	-0.06	0.08	-0.15	0.02	1.00		
	(60-day)	0.49	0.13	0.03	0.31	-0.08	0.01	1.00		
Diff 10y	(1-day)	-0.03	-0.08	0.05	-0.01	0.04	-0.04	-0.06	1.00	
	(20-day)	-0.05	-0.15	0.07	0.01	0.00	-0.01	0.08	1.00	
	(60-day)	-0.03	-0.20	0.28	0.10	0.00	-0.22	0.24	1.00	
Diff 3m	(1-day)	0.03	0.05	0.07	0.01	-0.01	0.03	0.00	-0.06	1.00
	(20-day)	0.08	0.16	0.11	0.02	-0.13	-0.31	0.06	0.22	1.00
	(60-day)	-0.20	-0.05	0.30	0.02	-0.02	-0.52	0.09	0.61	1.00

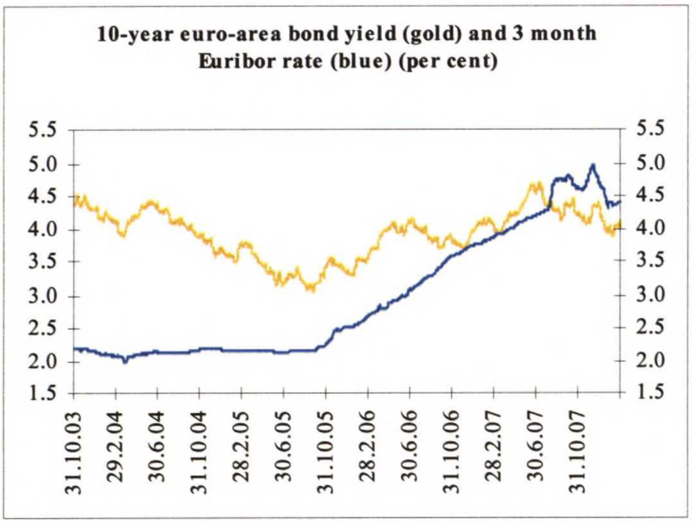
The above table presents the pairwise correlation matrix for USD/EUR. Each section is divided into 3 panels, illustrating the 1-day, 20-day and 60-day correlation matrixes of appropriate customer type or interest rate differential. The data period spans from October 31, 2003 to February 28, 2008. All positions are measured in EUR 10 million.

E. Graphical illustration of the data set

The following part presents detailed features of the data set, including the foreign exchange rates, government bond yields and short-term interest rates among others for all four different foreign exchange markets.

The following Fig. 7 presents the short and long term interest rates of the euro-area.

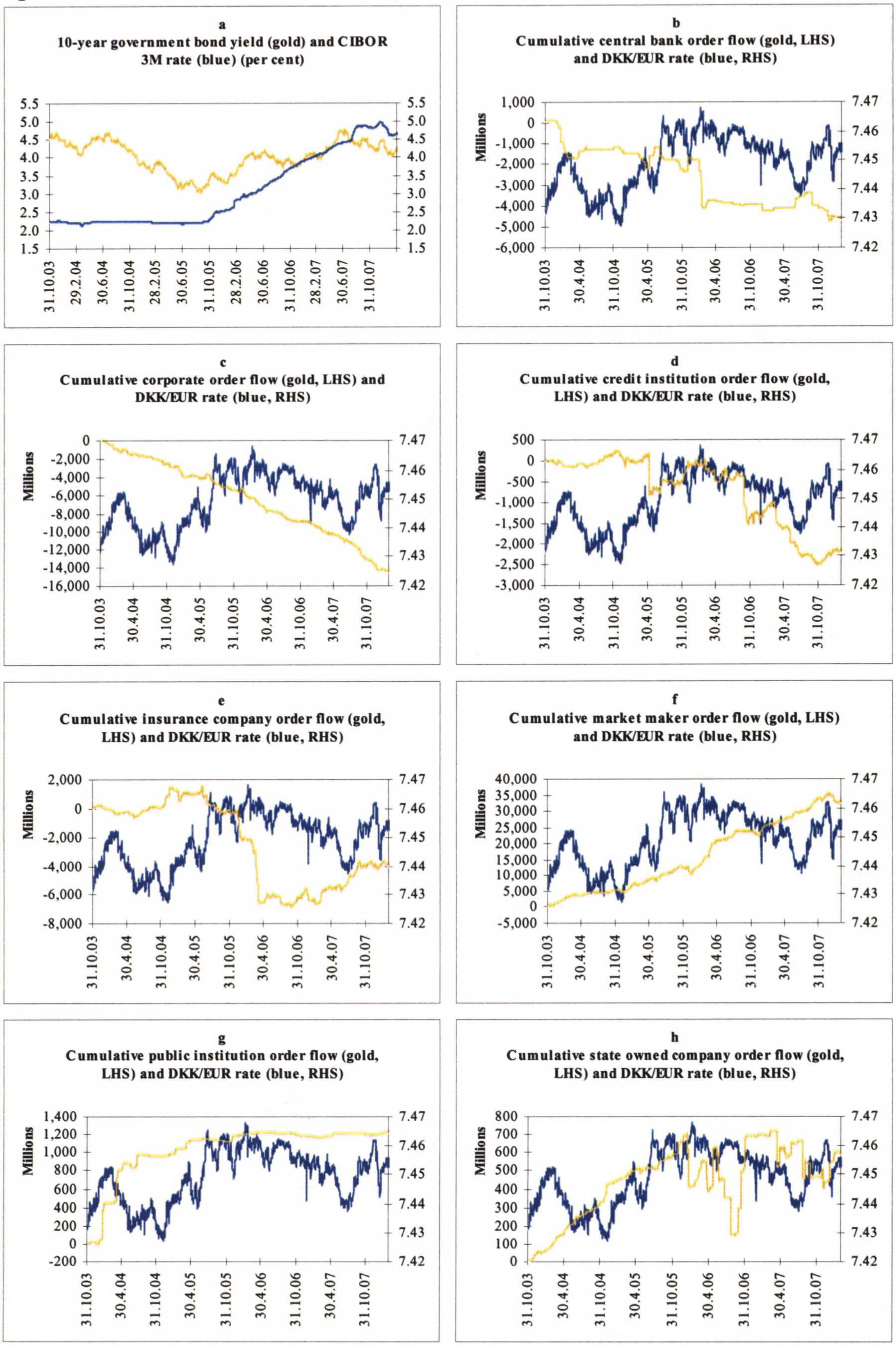
Figure 7 – Short and long term euro-area interest rates



The above figure presents the 3-month Euribor rate (blue) and the 10-year euro-area bond yield (gold). The data period spans from October 31, 2003 to February 28, 2008.

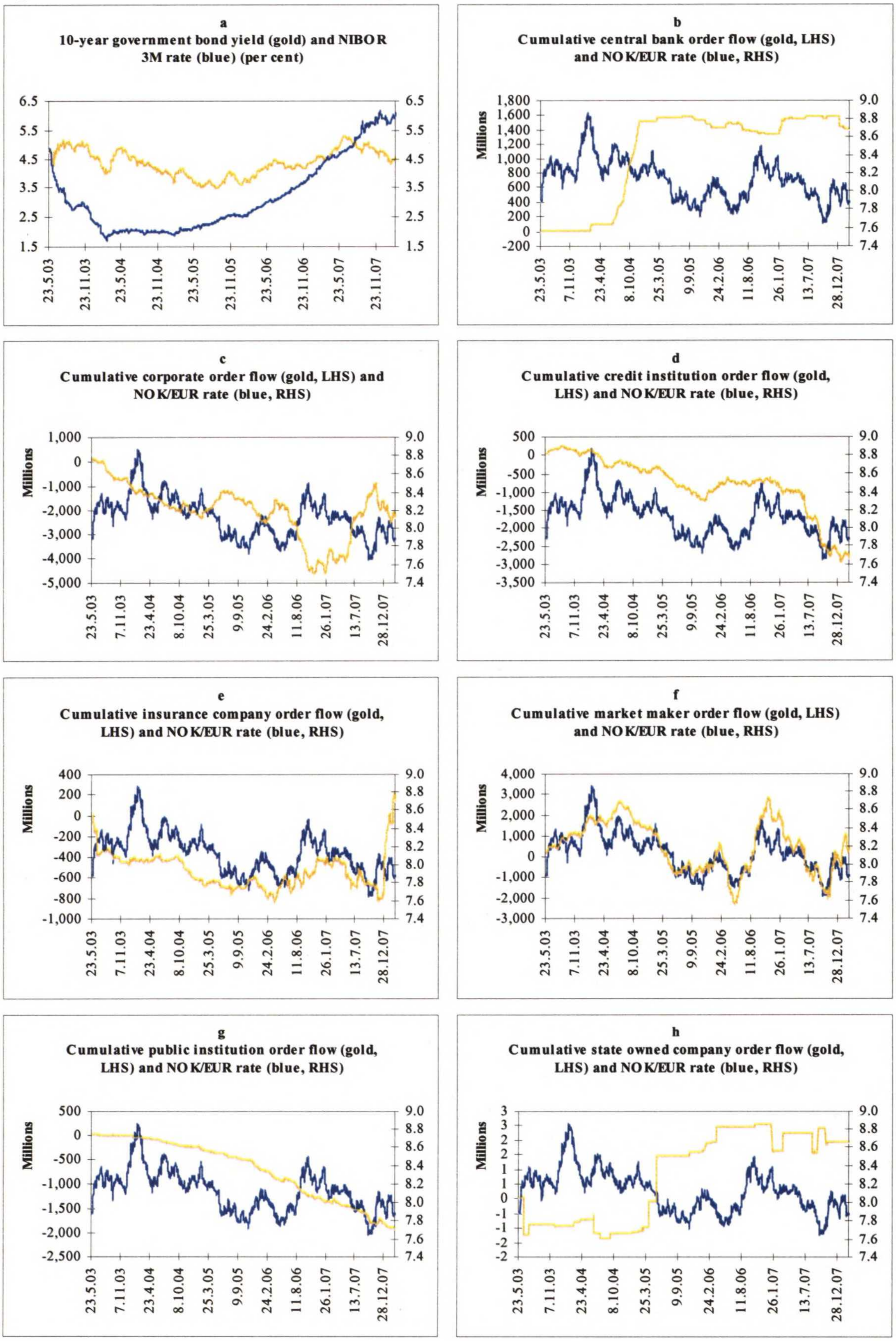
In all figures from 8 to 11 below, panel A illustrates the short and long term interest rates while panels from B to H present the cumulative order flow of different customer types (left axis) and the foreign exchange rate (right axis). The span of the data periods varies among different foreign exchange markets.

Figure 8 – Interest rates, DKK/EUR exchange rate and cumulative order flow of different customer types



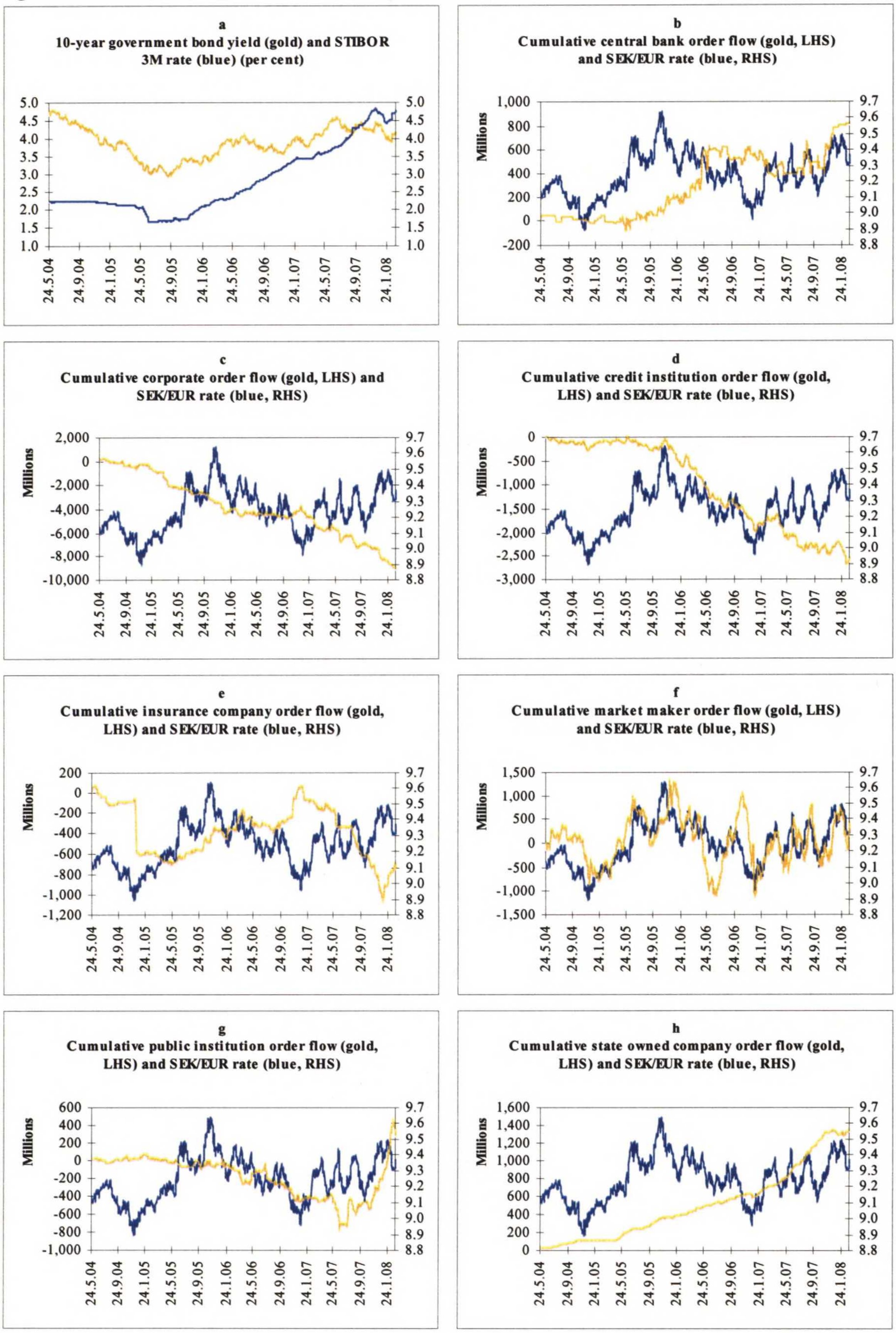
Panel A presents the short and long term interest rates and panels from B to H present the cumulative order flows of different customer types as well as the DKK/EUR exchange rate. The data period spans from October 31, 2003 to February 28, 2008.

Figure 9 – Interest rates, NOK/EUR exchange rate and cumulative order flow of different customer types



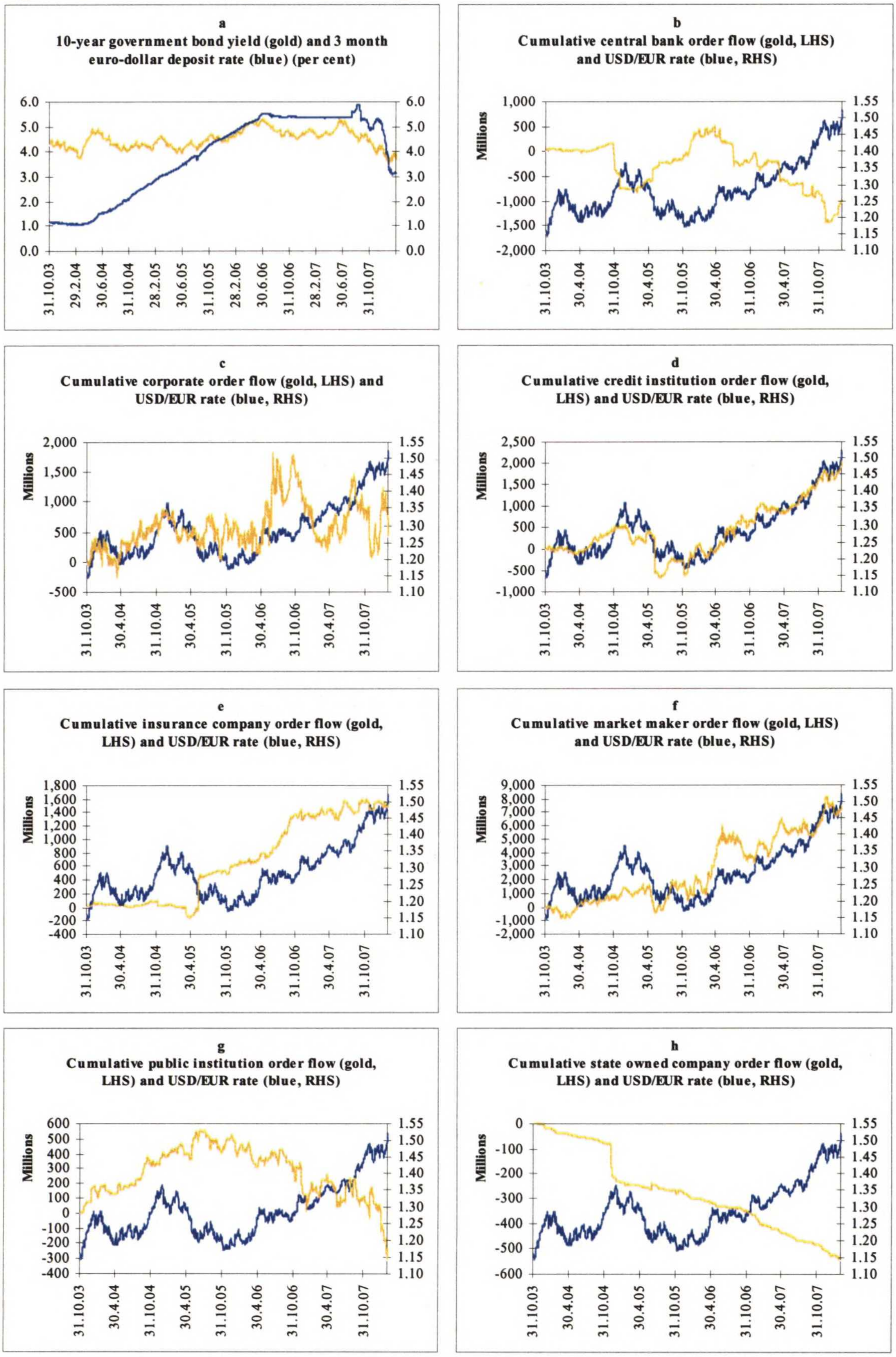
Panel A presents the short and long term interest rates and panels from B to H present the cumulative order flows of different customer types as well as the NOK/EUR exchange rate. The data period spans from May 23, 2003 to February 28, 2008.

Figure 10 – Interest rates, SEK/EUR exchange rate and cumulative order flow of different customer types



Panel A presents the short and long term interest rates and panels from B to H present the cumulative order flows of different customer types as well as the SEK/EUR exchange rate. The data period spans from May 24, 2004 to February 28, 2008.

Figure 11 – Interest rates, USD/EUR exchange rate and cumulative order flow of different customer types



Panel A presents the short and long term interest rates and panels from B to H present the cumulative order flows of different customer types as well as the USD/EUR exchange rate. The data period spans from October 31, 2003 to February 28, 2008.

F. Mathematical solution to the model

According to Evans and Lyons (2001), each market maker maximizes a negative exponential utility function defined over periodic wealth, and determines quotes and speculative demand based on this utility function. As returns have an unchanging stochastic structure and they are independent across periods, the market makers' problem disintegrates to a series of independent trading problems which occur once every period. Let W_{it} denote the wealth of market maker *i* and the round end *t* with the convention that W_{i0} denotes wealth at the end of period t-1. Using this notation and normalizing the gross return on the riskless asset to one, according to Evans and Lyons (2001), the market makers' problem can be written as:

$$Max \quad E\left[-\exp(-\theta W_{i3}|\Omega_i)\right] \qquad \{P_{i1}, P_{i2}, P_{i3}, T_{i2}\} \qquad \text{(A1)}$$

s.t.

$$W_{i3} = W_{i0} + c_{i1}(P_{i1} - P_{i2}^{'}) + (D_{i2} + E\left[T_{i2}^{'}|\Omega_{i2}\right])(P_{i3} - P_{i2}^{'}) - T_{i2}^{'}(P_{i3} - P_{i2}) \qquad \text{(A2)}$$

Here P_{it} is market maker *i*'s quote of round *t* and an apostrophe (') denotes an interdealer quote or trade received by market maker *i*. According to Evans and Lyons (2001), the market maker's problem is defined over four choice variables: the three scalar quotes P_{i1}, P_{i2} and P_{i3}, and the market maker's outgoing interdealer trade in round 2, T_{i2}. This round 2 outgoing interdealer trade has three components:

$$T_{i2} = c_{i1} + D_{i2} + E\left[T_{i2}^{'}|\Omega_{Ti2}\right], \qquad \text{(A3)}$$

where D_{i2} is market maker *i*'s speculative demand in round 2 and E[T'i2|ΩTi2] is the market maker's attempt to hedge against incoming orders from other market maker's (in equilibrium, this term is zero), according to Evans and Lyons (2001). Finally, the last three terms in W_{i3} capture capital gains/losses from customer order c_{i1} in round 1, speculative demand D_{i2} in round 2 and position disturbance from incoming interdealer orders $T^{'}_{i2}$ in round 2. The conditioning information Ω_i at each decision node (3 quotes and 1 outgoing order) is summarized below.

$$\Omega_{Pi1} \equiv \left\{ {}_{k=1}^{t}\{r_k\}, {}_{k=1}^{t-1}\{\Delta x_k\} \right\}$$

$$\Omega_{Pi2} \equiv \{\Omega_{Pi1,ci1}\}$$

$$\Omega_{Ti2} \equiv \{\Omega_{Pi2}\}$$

$$\Omega_{Pi3} \equiv \{\Omega_{Pi2}, \Delta x_t\}$$

F.1. Conditional variances

The model's solution uses several conditional return variances frequently. According to Evans and Lyons (2001), these variances do not depend on the realizations of these conditioning variables e.g. they do not depend on market maker *i*'s realization of c_{i1}. Therefore, these conditional variances are common to all market makers and known in the first period. This conditional variances' predetermination is key to the derivation of optimal quoting and trading rules, according to Evans and Lyons (2001).

F.2. Equilibrium

The equilibrium concept Evans and Lyons (2001) use is Bayesian-Nash Equilibrium or BNE. Under this BNE, Bayes rule is used to update beliefs and strategies are sequentially rational given those beliefs.

Consider the first properties of optimal quoting strategies before solving for the symmetric Bayesian-Nash Equilibrium. The following propositions are according to Evans and Lyons (2001):

PROPOSITION 1: A quoting strategy is consistent with symmetric BNE only if the round 1 and round 2 quotes are common across dealers and equal to:

$$P_{1,t} = P_{2,t} = P_{3,t-1} + \beta_1 r_t, \tag{A4}$$

where $P_{3,t-1}$ is the round 3 quote from the previous period and r_t is the payoff innovation at the beginning of period *t*.

PROPOSITION 2: A quoting strategy is consistent with symmetric BNE only if the common round 3 quote is:

$$P_{3,t} = P_{2,t} + \beta_2 \Delta x_t, \tag{A5}$$

where the constant β_2 is strictly positive.

F.3. Proof of propositions 1 and 2

Evans and Lyons (2001) note that no arbitrage requires that all dealers post a common quote in all periods. Moreover, common prices require that quotes be conditioned on commonly observed information only. In rounds 1 and 2, this includes the previous period's price of round 3 plus the perpetuity values of the increment r_t to the periodic payoff R_t. This implies that market maker *i*'s quote in round 2 therefore cannot be conditioned on her realization of c_{i1}.

Following the proof of Evans and Lyons (2001), the equations that pin down the levels of the above three prices embed the market maker and customer trading rules. These trading rules must be consistent with equilibrium price when they are conditioned on public information. According to Evans and Lyons (2001), this implies the following key relations:

$$E[c_{i1}|\Omega_{Pi1}] + E[D_{i2}(P_{1,t})|\Omega_{Pi1}] = 0 \tag{A6}$$

$$E[c_{i1}|\Omega_{Pi1}] + E[D_{i2}(P_{2,t})|\Omega_{Pi1}] = 0 \tag{A7}$$

$$E[\textstyle\sum_i c_{i1}|\Omega_{Pi3}] + E[\Delta c_3(P_{3,t})|\Omega_{Pi3}] = 0 \tag{A8}$$

According to Evans and Lyons (2001), the first two equations (A6) and (A7) simply state that, in expectation, market makers must be willing to absorb the demand from customers. Furthermore, the third Eq. (A8) states that, in expectation, the public must be willing at the price of round 3 to absorb the aggregate portfolio shift of the day. Moreover, they state that these equations pin down equilibrium price as any price except that which satisfies each participant would generate net excess demand in the interdealer trading in round 2, which cannot be reconciled since market makers trade among themselves.

That $P_{1,t} = P_{2,t} = P_{3,t-1} + \beta_1 r_t$ follows directly from the fact that expected value of c_{i1} conditional on public information Ω_{Pi1} is zero, and expected speculative market maker demand D_{i2} is also zero at this price, which is unbiased and based on public information, according to Evans and Lyons (2001). More precisely, this statement postulates that the market maker's demand D_{i2} has this property; the below derivation of the optimal trading rule following Evans and Lyons (2001) shows that this is the case.

That $P_{3,t} = P_{2,t} + \beta_2 \Delta x_t$ follows from the fact that Δx_t is a sufficient statistic for the aggregate portfolio shift $\sum_i c_{i1}$ (denoted c_1) in the beginning of the day, according to Evans and Lyons (2001). Moreover, given that the aggregate portfolio shift must be absorbed by the public in round 3, $P_{3,t}$ must adjust to induce the necessary public demand. More specifically, for clearing the market the price of round 3 must satisfy:

$$\Delta c_3(P_{3,t}) = -c_1 \tag{A9}$$

Given the optimal rule for determining T_{i2} [established below, following Evans and Lyons (2001)], c_1 of each day is proportional to that day's interdealer order flow Δx:

$$c_1 = (1/\alpha)\Delta x \tag{A10}$$

and since the specification of c_3 is:

$$C_3 = \gamma\left(E\left[P_{t+1}^3 + R_{t+1} \middle| \Omega_3\right] - P_t^3\right), \tag{A11}$$

the change in the aggregate speculative holding, Δc_3, equals c_3 minus previous accumulated holdings, or:

$$\Delta c_3 = \gamma\left(E\left[P_{t+1}^3 + R_{t+1} \middle| \Omega_3\right] - P_t^3\right) - \left(\sum_{t=1}^{t-1} - c_{1,t}\right) \tag{A12}$$

According to Evans and Lyons (2001), because the last term in the above expression of the change in the aggregate speculative holding is proportional to the sum of the previous day's Δx_t's, this implies a market-clearing price in the round 3 of:

$$P_{3,t} = E\left[P_{3,t+1} + R_{t+1} \middle| \Omega_3\right] + (\alpha\gamma)^{-1}\left(\sum_{t=!}^{t} \Delta x_t\right) = \sum_{t=!}^{t} (\beta_1 r_t + \beta_2 \Delta x_t) \qquad \text{(A13)}$$

with $\beta_2 = (\alpha\gamma)^{-1}$, which is unambiguously positive. The above sum is the perpetuity value of the expected periodic payoff R_t adjusted for a risk premium determined by cumulative portfolio shifts, yielding Eq. (7) of the Section 5.4.7.:

$$\Delta P_t = \beta_1 \Delta R_t + \beta_2 \Delta X_t, \qquad (7)$$

where ΔP_t denotes the change in price from the end of round 3 in period t-1 to the end of round 3 in period t. Note that at the end of period t, conditional on available information, the expected change in price over the next period is zero; according to Evans and Lyons (2001), given the expected stream of payoffs R_t, the level of price is sufficient to maintain public absorption of all past portfolio shifts.

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